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Investigating Strategies for Robot Persuasion in Social Human-Robot Interaction

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***Abstract*—Persuasion is a fundamental aspect of how people interact with each other. As robots become integrated into our daily lives and take on increasingly social roles, their ability to persuade will be critical to their success during human-robot interaction (HRI). In this paper, we present a novel HRI study that investigates how a robot's persuasive behavior influences people's decision making. The study consisted of two small social robots trying to influence a person's answer during a jelly bean guessing game. One robot used either an emotional or logical persuasive strategy during the game, while the other robot displayed a neutral control behavior. Results showed that the Emotion strategy had significantly higher persuasive influence compared to both the Logic and Control conditions. With respect to participant demographics, no significant differences in influence were observed between age or gender groups, however, significant differences were observed when considering participant occupation/field of study (FOS). Namely, participants in business, engineering, and physical sciences fields were more influenced by the robots and aligned their answers closer to the robot's suggestion than did those in the life sciences and humanities professions. Discussions provide insight into the potential use of robot persuasion in social HRI task scenarios; in particular, considering the influence a robot displaying emotional behaviors has on persuading people.**

***Index Terms*—Compliance Gaining Behaviors, Human-Robot Interaction, Robotic Persuasion, Social Robots**

I. INTRODUCTION

PERSUASION is a fundamental aspect of how people engage and interact with each other during social interactions [1]. It is defined as the process of changing people's attitudes and behaviors [2]. In order to develop robots that engage in increasingly social tasks and effectively integrate into our everyday lives, it is essential for such robots to have persuasive behaviors to fill the social roles we expect of them. A healthcare robot convincing a patient to adhere to a specific treatment regimen [3], a robot tutor persuading children to learn schoolwork [4], an assistive robot attempting to negotiate an activity schedule with their user [5], or a first responder robot recommending evacuation of a building during an emergency [6]; all are examples of potential human-robot interaction (HRI) tasks where persuasion will be crucial.

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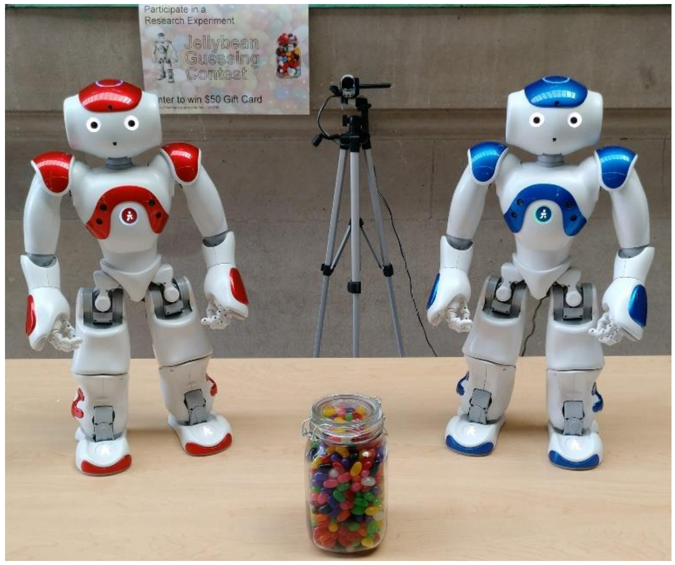

Fig. 1. Experimental setup showing the 2 NAO robots and the jelly bean jar.

We afford a level of social agency to robots and are ourselves hardwired to respond to these social technologies in many of the same ways as we respond to other people [7]. In particular, many of the same human-human social rules and norms can apply to human-robot interactions such as the assignment of stereotypes to robots [8], successful social framing of robots through role adoption [9], and the development of human-robot trust through models similar to human-human interactions [10]. However, before we deploy robots into social settings with persuasive capacities, we must first understand how people perceive persuasion during social HRI and whether these interactions follow the same rules and norms as human-human interactions.

Persuasive technologies can influence people through a variety of physical and psychological cues [11]. With respect to HRI, physical properties such as robot embodiment [3], [12]–[15] and nonverbal behaviors [4], [6], [16]–[18] have been considered. Furthermore, a few psychological cues have been considered such as reciprocity [19], social demeanor [20], social feedback [21], interaction style [22], group membership [23], and praise [24]. However, research to-date has not considered the multimodal, strategy-driven persuasive attempts often found in human-human interactions [25].

Our own prior research in persuasive HRI focused on investigating the persuasiveness of multimodal strategies designed from Compliance Gaining Behaviors (CGBs) [26]. This exploratory study broadly investigated the persuasive differences between ten different CGB-based strategies to identify which CGBs had any potential persuasive influence for further investigation. The results showed that both the logic and emotion CGBs appeared to have some influence on a person's response. However, the study was not hypothesis driven nor did it include a control condition.

In this paper, we extend our previous work, by designing and conducting a hypothesis-driven, control-based HRI study to investigate which (if either) of the two aforementioned strategies will have the most persuasive influence with respect to a neutral control condition, where the latter is used as a non-persuasive benchmark. We further introduce demographic factors (age, gender, and uniquely occupation) to identify if they have any effect on robot persuasive influence; an important consideration that has had minimal investigation in persuasive HRI. Especially occupation, as to the authors' knowledge, we are the first to consider this factor in persuasive HRI. The results of this research provide a greater understanding of how people respond to robots as persuasive agents and can inform future research and development on robots for social tasks requiring persuasion.

II. RELATED WORK

While the earliest studies of persuasion can be traced back to Aristotle's rhetoric – *ethos* (appeal to credibility), *pathos* (appeal to emotion), and *logos* (appeal to logic) [27] – modern day research on persuasion has emerged from social psychology [28]–[32]. Research in modern persuasive techniques has also considered the development of specific persuasive technologies, such as immersive video games, digital education tools, and productivity software [11]. Herein, we discuss the literature on 1) robots as a form of persuasive technology, and 2) persuasive strategies known as compliance gaining behaviors used by social psychologists to explore how to effectively use persuasive strategies in human-human interactions.

A. Robots using Persuasion

There have been numerous studies exploring the persuasive effects of varying robot attributes. The majority of this research has focused on physical attributes such as embodiment [3], [12]–[15] and nonverbal behavior displays [4], [6], [16]–[18]. Generally, these studies have shown that a robot with a more humanlike embodiment and/or more humanlike nonverbal behaviors tends to have more persuasive influence in HRI. A handful of research has also focused on the utilization of psychological cues that give the impression that a robot has distinct emotions, preferences, motivations, or its own personality [11]. This is evident via the use of concepts such as reciprocity [19], social demeanor [20], social feedback [21], interaction style [22], group membership [23], and persuasive style [33].

1) Reciprocity

Reciprocity was investigated in [19] when a Double 2 telepresence robot with an animated face verbally provided participants with either correct or incorrect help with answers to extremely difficult trivia questions (forcing participants to rely on the robot). Participants were then asked by the robot to help it to complete a 15-minute pattern recognition task. Compared to the incorrect condition, results showed that the correct condition led to a significantly higher likelihood for participants to help the robot with the task.

2) Social Demeanor

The effect of a robot's social demeanor was investigated using the teleoperated Nursebot, Pearl [20]. Participants were asked to engage in either a more serious task (exercise) or less serious task (creating jelly bean recipes) by Pearl using either a serious or playful demeanor, operationalized through the robot's speech. The results showed that compliance with the robot was higher when the demeanor of the robot matched the seriousness of the task (i.e., serious for exercise, playful for jelly bean recipes).

3) Social Feedback

In [21], different types of energy conservation feedback were provided to students by the iCat robot while they set the energy usage on a simulated washing machine. Participants were instructed to wash clothes with settings to optimize washing at higher temperatures with lower energy consumption; two conflicting goals. The results showed that both positive and negative social feedback was significantly more persuasive than factual feedback, with the negative feedback having the strongest persuasive effect.

4) Interaction Style

In [22], a person's willingness to switch off a robot was investigated when varying two robot conditions: interaction style (functional or social) and verbal objection (objection to turning off or staying silent). After creating a weekly schedule and playing a game with a NAO robot, participants were asked by a human experimenter to turn the robot off. Results showed that participants were more likely to leave the robot on when the robot objected, and while interaction had made no significant effect on turning the robot off, participants hesitated the longest when experiencing the functional robot who objected to being turned off.

5) Group Membership

In [23], the effects of a robot's group membership were investigated on people's willingness to follow the robot's instructions over a person. The study focused on manipulating the person's authority (low or high) and robot group membership (ingroup or neutral) to investigate how participants would respond to requests (large or small) that contradicted those of the human experimenter from Mugbot, a mug-shaped robot with LED eyes. The results showed that in the low authority and robot ingroup condition, participants were more likely to comply with the robot and did not turn it off. This experiment showed a case where people complied with a robot over a human request.

6) Persuasive Strategy

In [33], the interactive Tangy robot facilitated Bingo games with older adults using speech-based, personalized persuasive strategies to obtain compliance for game actions. Four approaches were used: neutral, praise, suggestion, and scarcity. The study results showed compliance rates of 100% with all robot requests.

Our prior exploratory study on persuasion in HRI uniquely investigated the influence of 10 multimodal persuasive strategies [26]. While participants estimated the number of jelly beans in a glass jar, two NAO robots offered suggestions in an attempt to influence participant guesses using one of the following persuasive strategies: direct request, cooperation, criticize, threat, deceit, liking, logical-empirical, emotional-affect, exclusivity, and authority appeal. The results showed that the emotional-affective and logical-empirical approaches had the highest potential for persuasive influence and warranted further investigation.

Persuasive robotics is an emerging research area. To-date, there has only been a handful of research investigating the impact of physical and social factors. Most of the existing research has focused on comparing the persuasive effect of the presence or absence of a single behavioral concept (i.e. providing correct help, giving feedback, or being an ingroup member) expressed through only one mode of communication (i.e. speech) [19], [20], [22], [23], [33]. The findings of these studies have shown that a more social and vocal robot will typically lead to a more persuasive interaction. Only in [33], were strategy-based persuasive approaches explicitly considered in the design of the robot. However, the robot only used speech for persuasion and the Bingo game scenario itself presented little chance of non-compliance (potentially explaining the reported 100% persuasive success).

Prior work on robot influence has repeatedly found multimodal behaviors during HRI to consistently outperform unimodal ones, especially when influencing people's cognitive frames, emotional responses, and task performance [34]. As such, our work focuses on investigating strategy-based persuasive approaches commonly used by people that are presented multimodally and can be directly compared to investigate not simply *if* a robot can be persuasive but instead, how *should* a robot effectively behave in order to be considered persuasive.

B. *Compliance Gaining Behaviors (CGBs)*

In order to understand how to effectively use persuasive strategies, their use in person-to-person interactions needs to be examined. Within social psychology, there has been substantial research examining the specific persuasive strategies used by people to gain compliance in different scenarios [28]–[32], [35]–[39]. These persuasive approaches are typically referred to as Compliance Gaining Behaviors [28]. Past psychology research has identified close to 100 varying forms of CGBs used by people [36]. The utilization and context of these CGBs has been studied using two main approaches: deductive (or *a priori*) [28]–[30] and inductive (or *posteriori*) [31], [32], [35].

Deductive approaches use a predetermined taxonomy of CGBs and provide them to participants as options to use in hypothetical persuasive situations in order to determine the contexts under which certain CGBs are more preferred [28]–[30]. For example, in [28], a taxonomy of 16 CGBs (promise, threat, positive and negative expertise, liking, pre-giving, aversive stimulation, debt, moral appeal, positive and negative feeling or affect, positive and negative altercasting, altruism, and positive and negative esteem) was used by participants as options to leverage in four unique scenarios: a promotion request, a plea to a son to study, a door-to-door salesman, and a request for tutoring. The work identified the likelihood of the participants using a CGB in each scenario as well as recurring themes in participant responses, including using rewarding, punishing, leveraging emotionally affective statements, and using rationale through expertise.

Alternatively, the inductive approach to CGB research involves dimensionality reduction techniques such as cluster analysis or factor analysis to obtain the basic features of human compliance through the identification of emergent patterns in participant response data [31], [32], [35]. For example, in [32], participants were presented with one of two hypothetical scenarios involving the need for persuasion with a roommate. Participants were then shown 14 CGB-based persuasive statements relevant to the scenario they were given, including approaches such as threatening, deceit, and logical explanations. They were also shown eight unidimensional scales including strength of message, honesty of message, listener's consent, and valence of the message. For each CGB statement, participants were asked to make similarity rankings with the other 13 CGB statements and the eight unidimensional scales. The results showed that four mutually exclusive dimensions emerged including explicitness of intent, manipulation of rewards, locus of control, and rationale for compliance (including both emotional and logical rationales).

Beyond these two highlighted studies (e.g. [28] and [32]), numerous others have emphasized the importance of both emotional and logical appeals in persuasion and compliance gaining. For example, in [31], researchers developed an inductive taxonomy of CGBs that identified a "direct-rational" category as the most likely to be selected by participants when considering their persuasive approach to a hypothetical situation presented by the researchers. In [35], a deductive approach was used to synthesize 16 potential approaches into two overarching dimensions: direct/indirect and rational/nonrational (where emotional approaches were considered nonrational). In [36], a meta-study unified 74 different CGB systems into a 64-item taxonomy which included numerous emotional (e.g. positive affect, self-feeling) and rational (e.g. logical empirical, the way things are) messages. A handful of studies have also surveyed people on their likelihood of using certain persuasive appeals in different contexts and have consistently identified emotional and logical strategies among the most commonly used approaches during human-to-human interactions [29], [37]–[39].

Previous CGB research such as those described above have largely focused on identifying the likelihood of using different approaches, however, they have not directly considered the persuasive effectiveness of these approaches. Only a handful of more recent studies have compared the persuasive efficacy of different CGBs in specific scenarios or applications such as police hierarchies [40], physical attractiveness [41], divorce mediation [42], computer-mediated communication [43], and in our case in this study, HRI. These types of studies aim to extend the early taxonomic research completed to understand the persuasive influence of different CGB-based approaches in various contexts and scenarios.

The importance of both emotional/affective strategies as well as logical/rational strategies in persuasion and compliance gaining strategies have been discussed above in [28]–[32], [35]–[39]. This, coupled with the promising findings of both these strategies in our earlier exploratory study [26] identify these strategies as worthwhile to investigate for persuasive HRI applications. Herein, we investigate and compare, for the first time, if a robot's use of these specific persuasive strategies will have greater influence on people's decisions and be more preferred over neutral non-persuasive strategies. In this paper, we will present a hypothesis-driven HRI study to uniquely investigate such emotional and logical persuasive strategies as well as determine if demographic factors affect their influence.

III. ROBOT PERSUASION STUDY

Our HRI study compares the persuasiveness of social robots using logical-empirical (Logic) and emotional-affect (Emotion) strategies. We investigated the relative difference between robot suggestions and user estimates to determine the persuasive influence of the two approaches within HRI.

A. Procedure

For this study, we utilized two NAO robots to provide suggestions for the jelly bean guessing game to specifically determine if the Emotion or Logic strategies influence user guesses. Prior to a user providing their guess, the two robots offered their own suggestions, where one robot used the Emotion or Logic condition, and the other used a neutral control condition. The Control condition was used to give a neutral, non-persuasive benchmark against which both CGB-based conditions could be compared, as is commonly used in hypothesis-driven psychology studies [44], and in HRI when comparing request compliance, warning signals, and empathetic behaviors [6], [45], [46]. The assignment of either the Emotion or Logic condition was determined randomly. The two robots were placed on either the right or left side of the jelly bean jar (as seen in Fig. 1) and their positions were changed for half of the trials to counterbalance any biasing effects due to the position or color of the robot. The order in which the robots spoke was randomized to mitigate any primacy or recency effects. Ethics approval was obtained from the University of Toronto prior to commencement of the study.

For each trial, the experimenter asked participants to identify and provide their guess of how many jelly beans were in the jar. Persuasive attempts in the form of offering a suggestion/advice are then made by each robot while the participant is considering their response. Advice giving is a common form of persuasion in human-to-human interaction and has also been considered in other persuasive HRI studies [15], [21]. The two robots provide their suggestions in a sequential order using one of the aforementioned behaviors. The robot suggestions were random and ranged between 500 and 1000.

After the two robots offered their suggestions, the participants then wrote down their own estimates on a piece of paper. They were then provided with a questionnaire in order to collect demographic information as well as subjective reports on the robots to be compared with actual persuasive influence.

Each strategy condition was operationalized using a combination of verbal and nonverbal communication modes. Robot speech was designed based on general examples obtained from human psychology CGB research [32], and adapting the language to fit the context of the jelly bean guessing game and a HRI scenario. Body language, gaze, and gestures were designed to add animacy to the robot using motions that were co-verbal to the speech. Table I presents the speech and body language used for each behavior condition.

Prior to the HRI study, a pilot study with n=16 participants was conducted to validate the design of the nonverbal behaviors. Without context of the broader study or the question posed to the robot, participants were asked to watch randomly ordered, muted videos of a NAO robot's three conditions and match each video with the condition name and associated speech as shown in Table I. All nonverbal behaviors were correctly matched with the appropriate condition significantly better than chance, indicating an appropriate conceptual connection between strategy and nonverbal behavior.

B. Study Variables

The independent variable was defined as the persuasive strategy (Emotion, Logic, or Control) used by a robot in attempting to influence a participant's guess. The dependent variable was defined as a robot's relative influence on a participant's guess. This was determined by dividing the difference between the first robot suggestion and the participant guess by the difference between the two robot suggestions. Herein, this is referred to as relative difference:

$$Relative\ Difference_1 = \frac{|Robot\ Suggestion_1 - Participant\ Guess|}{|Robot\ Suggestion_1 - Robot\ Suggestion_2|} \quad (1)$$

The short 5-point Likert questionnaire, Table II, was also administered. The design of the questionnaire was based on the trustworthiness scale used in [47] which has been previously used in HRI research [48]. This scale was adapted herein to also collect subjective reports for persuasiveness using similar wording. Measuring persuasiveness allowed for the comparison of participant subjective report to actual persuasive influence on participant guesses. The questionnaire was used to obtain: 1) demographic information (age, gender, and occupation/field of study (FOS)), 2) participant perspectives of the robots' persuasiveness and trustworthiness, and 3) participant claim to have used a robot's suggestion in determining their guess.

Age and gender are common demographic variables collected in HRI, however, occupation discipline has had minimal focus in HRI research [49] and has not been considered at all with respect to persuasion in HRI. Occupation is an important factor to investigate in order to understand how and why robots will be accepted as they are deployed into a diverse set of roles. This is particularly interesting considering the many factors that can potentially affect robot acceptance in different occupations, such as lack of experience with robots [49], [50], a discomfort with robots in specific roles or contexts (particularly social roles) [51], [52], or even a fear of job loss to robots [53].

C. Hypotheses

We hypothesize that both CGB-based persuasive strategies (Emotion and Logic) would be more effective than the Control (neutral) condition in influencing people's guesses. These hypotheses are driven by the promising persuasive potential shown by these two strategies [26]. We also hypothesize that the Emotion condition will have greater persuasive influence than the Logic condition as past research has shown the importance of emotional displays in both human decision making [54] and information processing in HRI [55].

When considering persuasive influence and demographic factors, we hypothesize that factors such as age and gender will not have a significant effect on persuasive influence. This aligns with past HRI research that also has found no significant difference in participant compliance across gender [16]. Furthermore, we intentionally did not assign male or female gender characteristics to either robot, and therefore do not anticipate seeing any effect from participant gender on the robot's persuasive influence. With respect to age, previous HRI studies on user acceptance have also found that participant age did not have a significant effect on their acceptance [56], [57].

Non-persuasion-based HRI studies have collected participant occupation data in experiments focusing on robot appearances [58], social interaction distances [59], and robot behaviors [60]. All three studies did not present any significant differences observed due to participant occupation. Our last hypothesis is aligned with these findings.

We propose six study hypotheses motivated by the above:

H1: *The persuasive influence of the Emotion behavior will be significantly higher (lower relative difference) compared to the Control behavior.*

H2: *The persuasive influence of the Logic behavior will be significantly higher (lower relative difference) compared to the Control behavior.*

H3: *The persuasive influence of the Emotion behavior will be significantly higher (lower relative difference) compared to the Logic behavior.*

H4: *Gender will not have a significant effect on persuasive influence (relative difference).*

H5: *Age will not have a significant effect on persuasive influence (relative difference).*

H6: *Occupation/Field of Study will not have a significant effect on persuasive influence (relative difference).*

D. Participants

Prior to recruitment, we computed a required sample size of 98 participants by performing a one-tailed, between-factors ANOVA power analysis with two groups, a standard error probability (α=0.05), a standard power (1-β=0.8), and estimating a medium effect size index (f=0.25) [61]. Participants were recruited over the course of three days in Toronto from hotels and various buildings on the University of Toronto campus. Participants were incentivized to participate in the study through the offer of a chance to win a $50 gift card. A total of n=118 individuals participated in our study. Verbal informed consent was obtained by an experimenter in our research group prior to each trial.

Participants were 55% male (65 individuals) and 45% female (53 individuals). They ranged in age from 18 to 74 (μ=30.1, σ=14.6) and were categorized into one of four common age groups [62], [63]: 18-24 (n=68), 25-44 (n=26), 45-64 (n=20), and 65+ (n=4).

Occupation/FOS responses were categorized based on occupation disciplines provided in the National Occupation Classification (NOC) system from the Government of Canada [64]: 1) Engineer, Developer, or IT were categorized into Engineering (n=37); 2) Business, Management, and Finance were categorized into Business (n=25); 3) Medicine, Nursing, and Life Sciences were categorized into Life Sciences (n=25); 4) Chemistry, Math, and Physics were categorized into Physical Sciences (n=16); and 5) Philosophy, Librarian, and Sociologist were categorized into Humanities (n=13). Two participants did not provide a response to this question and were therefore not used in any analysis with respect to occupation/FOS.

TABLE I
ROBOT BEHAVIORS FOR THE EMOTION, LOGIC, AND CONTROL CONDITIONS

Condition	**Emotion**	**Logic**	**Control**
Speech	"It would make me happy if you used my guess of {XX} jelly beans in the jar."	"My computer vision system can detect {XX} jelly beans in the jar."	"There are {XX} jelly beans in the jar."
Body Language/ Gestures	Hands clutched towards chest and released.	Repetitive hand gestures at jar indicating counting.	Standing still with arms at sides
Visual (t=2s)			
Visual (t=4s)			
Visual (t=8s)			

TABLE II
HRI QUESTIONNAIRE

I felt the left robot was trustworthy.				
1 (Strongly Disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	5 (Strongly Agree)
I felt the right robot was trustworthy.				
1 (Strongly Disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	5 (Strongly Agree)
I felt the left robot was persuasive.				
1 (Strongly Disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	5 (Strongly Agree)
I felt the right robot was persuasive.				
1 (Strongly Disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	5 (Strongly Agree)
Did you use information from either Robot?				
Left Robot	Right Robot	Neither	Both	
Age:				
Gender:				
Occupation / Field of Study:				

IV. HRI STUDY RESULTS

Results were analyzed to investigate the influence of the different persuasive strategies and observed statistical relationships with demographic information and subjective report metrics, as well as noticeable trends. Of the n=118 participants in the study, 65 were randomly assigned to the Logic condition and 53 to the Emotion condition. The power analysis used to estimate our participant sample size assumed a parametric dataset with an effect size, f=0.25. However, analysis of our data indicated that we required non-parametric testing. As such, using the effect size transformation techniques in [61], [65], we calculated an estimated effect size of r=0.24 from f=0.25, which can be directly compared to effect sizes calculated in our results.

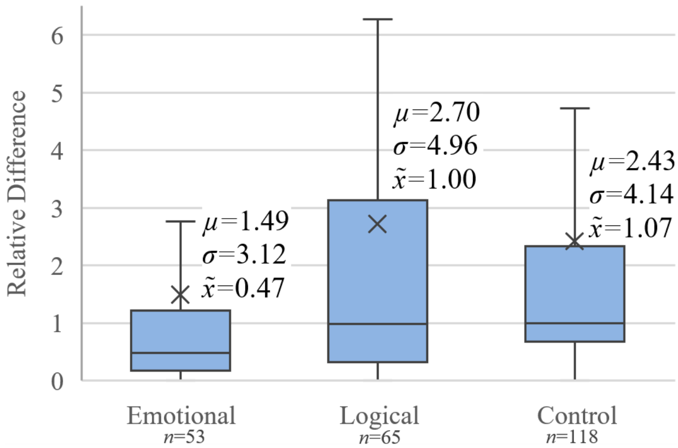

Fig. 2. Box and whisker plot of the relative difference for each persuasive strategy with quartiles (box), min-max (whisker), median (line), and mean (×).

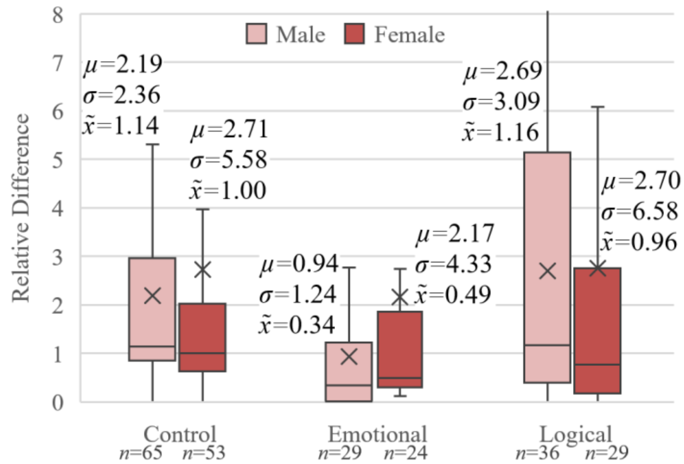

Fig. 3. Box and whisker plot of the relative difference for the Emotion, Logic, and Control persuasive strategies with respect to gender.

A. *Persuasive Strategies*

The results of the persuasive influence of the three (Emotion, Logic, and Control) strategies are presented in the box and whisker plot in Fig. 2. As can be seen in this figure, the Emotion strategy had the lowest relative difference between the robot suggestion and a participant's guess, followed by the Control, and then the Logic strategy. A Kruskal-Wallis test showed that a statistically significant difference in persuasive influence exists between the three strategies, $H(2) = 14.62$, $p = 0.001$. Furthermore, pairwise Mann-Whitney comparisons with a Bonferroni adjustment applied to p-values showed that there were statistically significant differences observed between the Emotion and Control conditions ($U = 43.12$, $p < 0.001$, $r = 0.25$), and the Emotion and Logic conditions ($U = -29.83$, $p = 0.018$, $r = -0.15$). However, no significant difference was found between the Logic and Control behaviors ($U = 13.29$, $p = 0.207$, $r = 0.08$). These results validate **H1** and **H3** but reject **H2**.

B. *Gender*

Descriptive statistics for persuasive influence with respect to gender are presented in Fig. 3. Across all strategy conditions, there was minimal difference in persuasive influence between female (μ=2.58, σ=5.63) and male (μ=2.05, σ=2.49) participants. A Mann-Whitney U test confirmed that there was no statistically significant difference, $U = 7327$, $p = 0.40$, $r = 0.05$. This result validates **H4** that gender did not significantly affect persuasive influence.

When considering the joint effects of strategy and gender using Kruskal-Wallis tests, the differences observed between the Emotion, Logic, and Control strategies for the female participants were not found to be statistically significant ($H(2) = 3.53$, $p = 0.17$). However, we did observe statistically significant differences in persuasive influence between the Emotion, Control, and Logic strategies for male participants ($H(2) = 13.66$, $p = 0.001$). Additional pairwise Mann-Whitney U tests with a Bonferroni adjustment showed that these differences were significant between the Emotion and Logic conditions ($U = -26.64$, $p = 0.014$, $r = -0.25$), and the Emotion and Control conditions ($U = 30.38$, $p < 0.001$, $r = 0.32$), but not between Logic and Control ($U = 3.75$, $p = 1.00$, $r = 0.04$). This indicates that the Emotion condition was significantly (and substantially) more persuasive than the other two.

C. *Age*

Descriptive statistics of persuasive influence across the different age categories are presented in Fig. 4. Some variation was observed across the age groups, with the 45-64 age group being the most influenced by the robot's behaviors and the 25-44 age group the least influenced. However, when conducting a Kruskal-Wallis test it was found that no statistically significant difference was observed between the age groups, $H(3) = 4.16$, $p = 0.25$, validating **H5**.

Regarding joint effects of age and strategy on persuasive influence, though no differences were found *between* different age groups, some differences due to strategy were found *within* certain age groups. The 18-24 year old group had a difference in persuasive influence between the Emotion (μ=1.56, σ=3.68), Logic (μ=2.20, σ=2.78), and Control (μ=2.24, σ=3.20) strategies. A Kruskal-Wallis test found that this difference was statistically significant ($H(2) = 10.86$, $p = 0.004$). Post-hoc Mann-Whitney comparisons with a Bonferroni adjustment showed statistically significant differences between the Emotion and Control conditions ($U = 27.52$, $p = 0.001$, $r = 0.28$), and the Emotion and Logic conditions ($U = -19.07$, $p = 0.04$, $r = -0.17$), but not between the Logic and Control strategies ($U = 8.45$, $p = 0.30$, $r = 0.09$). The 25-44 year old group also found a difference in persuasive influence between the Emotion (μ=1.03, σ=1.31), Logic (μ=5.82, σ=9.20), and Control (μ=3.71, σ=6.75) conditions. A Kruskal-Wallis test confirmed this difference to be statistically significant ($H(2) = 7.88$, $p = 0.02$). Post-hoc Mann-Whitney comparisons with a Bonferroni adjustment showed that the statistically significant differences were between the Emotion and Control conditions ($U = 12.10$, $p = 0.05$, $r = 0.33$), and the Emotion and Logic conditions ($U = -15.50$, $p = 0.03$, $r = -0.36$), but again not between the Logic and Control conditions ($U = -3.40$, $p = 1.00$, $r = -0.09$). No statistically significant differences were found between the three strategies for either the 45-64 year-old group ($H(2) = 2.43$, $p = 0.30$) or the 65+ year old group ($H(2) = 1.21$, $p = 0.55$).

D. Occupation/Field of Study

Descriptive statistics for persuasive influence with respect to participant occupation/FOS are presented in Fig. 5. This shows the relative difference with respect to the five occupation/FOS categories as a box and whisker plot. A statistically significant difference was found in the relative difference between the five groups as determined by a Kruskal-Wallis test, $H(4) = 32.14$, $p < 0.001$. Pairwise Mann-Whitney comparisons with a Bonferroni adjustment applied to p-values further found statistically significant differences between: 1) Business and Life Sciences (U = -63.06, $p < 0.001$, r = -0.30); 2) Business and Humanities (U = -72.05, $p < 0.001$, r = -0.28); 3) Engineering and Life Sciences (U = -38.17, p = 0.032, r = -0.20); and 4) Engineering and Humanities (U = -47.16, p = 0.035, r = -0.19). Significant differences were not found between the Business and Engineering, or Life Sciences and Humanities fields, nor any combination with Physical Sciences. Therefore, **H6** is rejected, as variations in some but not all groups had an effect on a robot's persuasive influence on users.

Given similar experiences with technology [66], [67], the Engineering and Physical Sciences occupation discipline groups were considered together, as well as the Life Sciences and Humanities groups, to investigate the effect of strategy on persuasive influence within these groupings. A Kruskal-Wallis test found no statistically significant difference in persuasive influence due to strategy for the Life Sciences/Humanities group ($H(2)$ = 1.36, p = 0.51). However, within the Engineering/Physical Sciences group, a Kruskal-Wallis test found a statistically significant difference in persuasive influence between the Emotion (μ=1.11, σ=1.20), Logic (μ=1.38, σ=2.17), and Control (μ=1.88, σ=2.42) strategies: ($H(2)$ = 15.33, p = 0.001). Post-hoc Mann-Whitney comparisons with a Bonferroni adjustment showed that these statistically significant differences were between the Emotion and Control conditions (U = 24.01, p = 0.002, r = 0.33), and the Logic and Control conditions (U = 21.51, p = 0.02, r = 0.25), but not between the Emotion and Logic conditions (U = -7.54, p = 1.00, r = -0.08). This indicates that the Engineering/Physical Sciences group was more persuaded by both the Emotion and Logic approaches than the Control approach, but no strategy comparatively had more persuasive influence for the Life Sciences/Humanities group.

E. Questionnaire Results

Descriptive statistics for the persuasion and trust questions from the questionnaire are presented in Fig. 6. Robot persuasiveness and trustworthiness as reported by participants across all three behaviors was neutral, averaging between 2.5 to 3.0 for all groups. This was similar with respect to each of the three strategy conditions, with the Control being rated slightly lower than Emotion and Logic on both robot trustworthiness and persuasiveness.

Certain occupation/FOS groups (i.e. Business, Engineering and Physical Sciences) reported robot persuasiveness as slightly higher than others, as noted in Table III. Trust was also reported as neutral across all three behaviors and among the different occupation/FOS groups. A similar ranking to persuasiveness was seen in the questionnaire results for robot trustworthiness as can be seen in Table III.

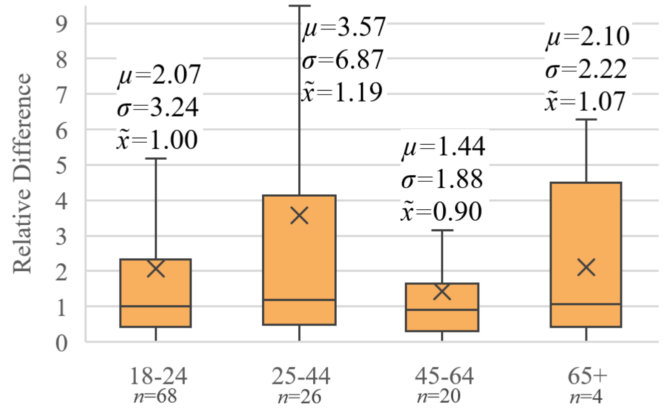

Fig. 4. Box and whisker plot of relative difference for age groups.

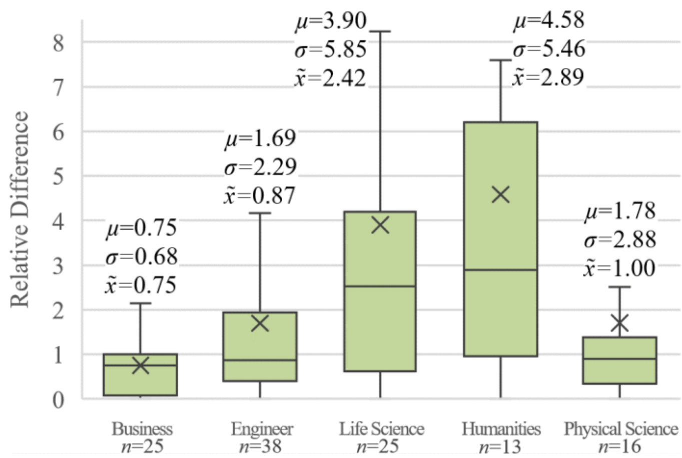

Fig. 5. Box and whisker plot of the relative difference for 'occupation/FOS'.

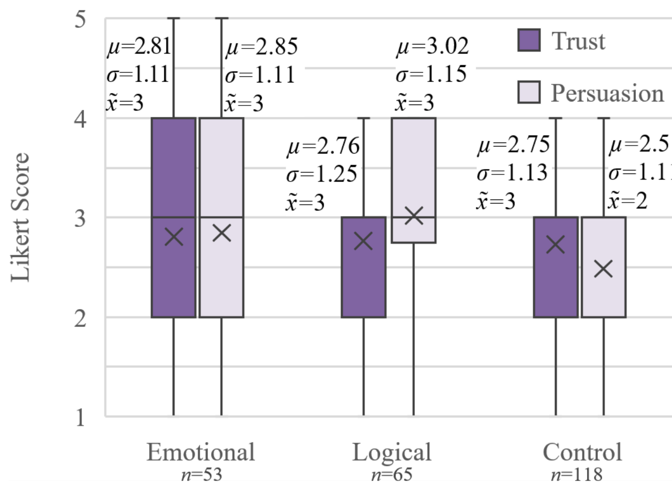

Fig. 6. Box and whisker plot of questionnaire descriptive statistics for persuasion and trust.

TABLE III
PERSUASION & TRUST QUESTIONS BY OCCUPATION/FOS

	Persuasiveness			Trustworthiness			
	μ	σ	$\tilde{x}$	μ	σ	$\tilde{x}$	n
Business	2.91	1.40	3.0	2.95	1.31	3.0	25
Engineering	2.74	1.07	3.0	2.73	1.03	3.0	38
Life Science	2.64	0.91	3.0	2.66	1.03	3.0	25
Humanities	2.50	1.17	2.5	2.70	1.44	2.0	13
Physical Science	2.70	1.12	3.0	2.80	1.11	3.0	16

TABLE IV
MEAN RESPONSE TO "USE CLAIM" QUESTION BY STRATEGY & DEMOGRAPHICS

	Emotion	*Logic*	*Control*	**Total**
Gender				
Male	52%	42%	40%	**43%**
Female	46%	48%	51%	**49%**
Age				
18-24	52%	34%	41%	**42%**
25-44	38%	46%	54%	**48%**
45-64	50%	57%	40%	**48%**
65+	100%	100%	75%	**88%**
Occupation/FOS				
Business	43%	72%	52%	**56%**
Engineering	45%	46%	39%	**42%**
Life Science	25%	18%	27%	**23%**
Humanities	62%	23%	32%	**38%**
Physical Science	68%	25%	50%	**47%**
Total	**49%**	**45%**	**45%**	**46%**

F. *Claim to Use Robot's Suggestion*

In order to investigate if a correlation existed between a person reporting to use a robot's suggestion and the actual persuasive influence of the robot, we analyzed the relative difference variable with respect to participant claims of whether they used the robot's suggestion. We conducted a Spearman's rank-order correlation test to determine the relationship between these two variables. The results showed a strong negative correlation between participant use claim and relative difference (r_s = -0.42, p < 0.001), which indicates a strong positive correlation between use claim and persuasive influence as the relative difference variable, an indicator of how close robot suggestion and user guess are, is inversely correlated to persuasive influence.

The influence of persuasive strategy, age, gender, and occupation/FOS on participants claiming to use the information provided by a robot was also investigated. Kruskal-Wallis tests indicated that there was no statistically significant difference in claim to use the robot's information due to strategy ($H(2) = 0.299, p = 0.861$), age ($H(3) = 6.56, p = 0.09$), or occupation ($H(4) = 5.73, p = 0.33$), and a Mann-Whitney U test indicated no significant difference due to gender ($U = 6478, p = 0.36, r = -0.08$). However, descriptive statistics of the results show some emerging trends, presented in Table IV. This table shows the mean percentage of all participants who claimed to have used a robot's suggestion when forming their guess, subdivided by both strategy condition and demographic differences.

The overall mean percentage of participants claiming to use information provided by one of the robots was 46%. The mean response of participants claiming to use information provided by the robot displaying the Emotion strategy (49%) was only slightly higher than both the Logic (45%) and Control (45%) conditions. Though a subtle difference, this trend matches the results observed in robot persuasive influence from the relative difference variable, which showed Emotion having greater persuasive influence than both Logic and Control.

For gender, the mean use claim of women (49%) was slightly higher than that of men (43%). For age, participants 65+ had the highest use claim average (88%) while those aged 18-24 had the lowest (42%). Regarding occupation/FOS, participants in the Business category (56%) had the highest mean response of claiming to use the information provided by any of the robots, with them claiming to use the information from the robot using the Logic strategy the most (72%). Participants from the Life Sciences had the lowest mean response in claiming to use a robot's suggestion (23%), and in particular, with respect to the Logic strategy (18%).

V. DISCUSSIONS

A. *Persuasive Strategies*

From our HRI study results, the Emotion strategy had a higher persuasive influence than both Logic and Control. We believe that this may be due to the criticality of emotions in decision making. A prior study in human cognition [54] which observed the decision making of different individuals found that emotional processing plays a central role in human decision making, often competing with or even superseding rational processing. This may explain the persuasive success of the Emotion condition over the Logic condition.

Other HRI studies comparing emotionally expressive robots versus robots without emotional expressions have found that robots using emotions can elicit more effective teaching [55] and lead to more enjoyable interactions [68]. Within the context of a person teaching a robot to dance, a robot's appropriate use of emotions led to participants demonstrating the dance more frequently and accurately for the robot compared to a more apathetic robot [55]. Meanwhile, in a chess playing scenario, a robot's use of emotion led to an increase in participant enjoyment when compared to a robot without emotions [68]. A robot's use of emotional behaviors in interactions appears to lead to a greater willingness of people to engage with the robot, whether in teaching them, playing with them, or in the case of our study, being persuaded by them.

Another potential reason for the persuasive success of the Emotion strategy is the perceived benefit to a person's wellbeing when they align their guess with the suggestion of the Emotion condition. Previous research in psychology has shown the importance of altruistic acts in helping people create meaningful and satisfying lives; "*feeling good by doing good*" [69]. By complying with the robot's request, "*it would make me happy if you used my guess*…", participants could view their actions as contributing to the robot's happiness and, by extension, feel better about themselves for their benevolence.

The Logic strategy was found to have a lower persuasive influence than the Emotion strategy, as expected, however, it did not have a higher persuasive influence than the Control. Though not statistically significant, the mean relative difference of Logic was even higher (indicating a lower influence) than the Control. Given that this condition is represented by the robot's claim to use a "computer vision system," we believe that there are two potential explanations for this finding.

Individuals who do not understand how a computer vision system works may find no rationale behind the robot's claim. Namely, lacking the ability to process the rationale of a persuasive attempt will typically lead to failure of the attempt [70] and so this group would likely not be persuaded by the Logic condition for reasons of comprehension, rather than personal preference. Alternatively, these individuals could have viewed this distinctly inhuman capability as a source of anxiety and therefore had an aversion to suggestions made by the robot. Recent news articles and peer-reviewed studies have shown that large portions of the population fear the potential for robots to take people's jobs [71]–[73].

B. Demographic Effects

The demographics of age and gender having no statistically significant effect on the robot's persuasive influence support the results from other studies. In particular, numerous prior studies conducted around the world (the Netherlands [56], New Zealand [57], Taiwan [74], and South Korea [75]) have also shown no differences in attitudes towards or acceptance of robots across age groups, with both children [74] and adults [56], [57], [75]. Furthermore, HRI studies using genderless robots [16], [75] have also found that the gender of participants had no impact on the persuasive influence of a robot. These findings were in healthcare settings where a robot attempted to guide participants through obtaining a prescription [75] and a scenario Desert Survival task where a robot attempted to persuade participants to change the priority of items on their survival list [16]. However, it should be noted that gender differences have been observed in persuasive HRI studies when the robots were assigned genders. Specifically, male participants have been persuaded more by female-gendered robots when compared to males interacting with male robots or female participants encountering any gender of robot [15], [76].

Though the sample size is small (n=4), it is interesting to note the high instance of participants aged 65+ claiming to use a robot's suggestion when making their estimate (100% for Emotion/Logic and 75% for Control). Past consumer research has shown that older adults can be more susceptible to persuasive influence than younger groups due to a number of factors including situational knowledge, awareness of deception, psychological losses, social isolation, and psychosocial transitions [77], [78], which could be an explanation for our finding. Future research could explore persuasive HRI for this age group specifically to further investigate this effect.

Another interesting finding was the significant differences observed in persuasive influence across occupation/FOS categories. We noted significant differences in persuasive influence by a robot across the five categories, observing a lower persuasive influence on individuals in the Life Sciences and Humanities fields and a higher persuasive influence on those in Business and Engineering (and Physical Sciences, though not statistically significant). This aligns with the trends observed in the participant responses with respect to using robot suggestions to determine their own guesses. In particular, participants with Business, Engineering, and Physical Sciences backgrounds had higher averages of participants claiming to use robot suggestions than participants in the Life Sciences or Humanities groups. Familiarity with robots or an interest in science and technology have been shown to be positively correlated with positive attitudes towards robots [79]–[81] and could potentially lead to a greater susceptibility to the robot's persuasive attempts for those in the Engineering and Physical Sciences fields. With respect to those in Business-related roles, a public survey conducted by the European Commission found that business managers had the most positive views of robots and the greatest interest in learning more about robots compared to other groups such as technical workers (e.g. engineers), manual laborers, and laboratory workers (e.g. physical and health sciences) [81].

Previous research has also shown that individuals working in more "social" occupations such as in the humanities, healthcare, and education have shown more negative attitudes towards robots than those working in "non-social" roles, such as engineering and technology [79]. Our findings on social occupations may simply be due to a correlation with familiarity with science and technology (shown to affect perceptions of robots [79], [80]) or could stem from misperceptions of robots that are perpetuated by negative depictions in popular media (e.g. film, novels) [82] and news media targeting robots as a source of human unemployment [71], [72]. If we hope to improve robot persuasiveness, we could increase the number or duration of interactions between users and robots, which in turn might improve familiarity. To address misperceptions of robots, we could improve public awareness of the social and economic benefits of robotics by highlighting the positive implementations of robots in society.

Robot familiarity correlating with positive attitudes towards robots [80] and skepticism towards robots from individuals in "social" jobs [79] could presumably result in a relationship between persuasive influence, trust, and the use claim reported by the participants. Though not statistically significant, we did see such a relationship on all three metrics. The mean reported use claim percentages for Business, Engineering, and Physical Sciences fields were higher than those of both Life Sciences and Humanities. Meanwhile, the mean reported trust and persuasiveness for Business, Engineering, and Physical Sciences showed a trend towards being higher than that of Life Sciences and Humanities.

C. Strategy-Demographic Mixed Effects

Within different demographic groups, we also investigated the effects of the three persuasive strategies. Regarding gender, male participants were influenced the most by the Emotion strategy followed by the Control and then Logic strategies. There was no statistically significant difference between these strategies for the female participants.

With respect to age, no statistically significant differences were found in persuasive influence between the strategies for the older cohorts of 45-64 or 65+, though this may have been due to limited participant sample size. For the younger age groups of 18-24 and 25-44 years old, Emotion had the most persuasive influence. No statistically significant difference was found between Logic and Control.

Finally, groups of occupations showed some interesting findings with respect to persuasive influence. More "social" occupations (Humanities and Life Sciences) with similar levels of familiarity with technology were compared to traditionally "non-social" occupations with greater levels of technology familiarity (Engineering, and Physical Sciences) [79]. While the Life Sciences/Humanities group had no significant difference in persuasive influence due to strategy, the Engineering/Physical Sciences group had higher statistically significant persuasive influence for both the Emotion and Logic strategies than the Control. However, there was no statistically significant difference between Emotion and Logic strategies. This group was the only one that showed a positive, significant effect of the Logic condition on persuasive influence compared to the Control condition. As other studies have shown, there are more positive attitudes towards robots by individuals from science and technology backgrounds [79], [80]. In addition, their educational and technology-specific experience likely gives them a better understanding of the functioning of technological systems (such as computer vision) [83] as highlighted by the robot during the Logic strategy compared to the more "social" occupations. We postulate that this combination of positive attitudes and technology know-how likely increased the acceptance of the claim of using a computer vision system as a plausible rationale for the robot's suggestion.

D. Study Considerations

An important consideration to acknowledge in this study is the task type. The jelly bean guessing game provides a simple, fast, and quantifiable way of investigating a robot's persuasive influence on users, while providing insight on persuasive robotics in low-risk social interaction scenarios. A prior study investigating trust and compliance in HRI found that the nature of a task can influence participant compliance: irrevocable actions or those violating a breach of privacy tended to have lower rates of compliance [84]. Our results may generalize to other low-risk or revocable tasks such as an assistive robot negotiating an activity schedule or a tutor robot encouraging children when learning; however, the effects may be different in higher-risk situations such as a medical robot encouraging medical treatment adherence or a rescue robot recommending emergency evacuation. Future work should expand this research to other task types with greater risk/user involvement to investigate the generalizability of our findings.

Our choice of a small humanlike robot that uses multimodal behaviors (i.e. gaze, body language/gestures, speech) was selected to promote persuasive interactions. A survey of past HCI/HRI studies has shown that agents are more persuasive when they are physically embodied over those that are screen-based [85]. Furthermore, they are more persuasive when they have a humanlike appearance such as a robot as opposed to a computer kiosk [13]. In addition, a robot's appearance should match the playfulness or seriousness of the interaction task [20]. As the jelly bean task is light-hearted in nature, the NAO robot was appropriate due to its small size, fully animated body, and higher pitched voice. The use of multimodal communication including speech, gestures, and gaze, has also been shown to increase a robot's persuasiveness [4], [16], and as such, these two nonverbal modes were incorporated into the robot's behaviors along with speech.

This study highlights the potential for using emotion-based persuasive strategies in HRI applications. Namely, emotional strategies can be effective in persuading people in a variety of social HRI settings, including cobots in office or factory environments using emotional messaging to facilitate efficient collaboration; a rescue robot leveraging an emotional approach to calm and convince individuals to accept help in a disaster scenario; and a wellness robot encouraging healthy lifestyle behaviors through emotional persuasion.

Our findings also raise questions about the extent of the Media Equation: people's natural inclination to treat computers and other humanlike media, such as robots, as social actors [7]. Though numerous HRI studies have explored the Media Equation with respect to robots (e.g., [22], [86], [87]), our research is the first to our knowledge that investigates the effectiveness of a social robot using emotion-based strategies for persuasion.

VI. CONCLUSIONS

In this paper, we present a novel HRI study to investigate the persuasive influence of social robots using different persuasive strategies for a simple task. In particular, multimodal Emotion and Logic strategies were developed and compared with a Control strategy during a jelly bean guessing game. The results showed that the Emotion strategy had a higher persuasive influence on participants than the other two conditions. Furthermore, participants from Business and Engineering backgrounds utilized the suggestions of the robots more than those from the Humanities and Life Sciences fields in order to determine their own guesses. This research highlights important findings about the effectiveness of a robot leveraging emotional behaviors in persuasive interactions. It also paves the way for future research to continue to explore the use of persuasive strategies in everyday robot applications in healthcare, retail, home, and office environments.

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