“It’s All About Confidence, Baby!”: Comparing the Effects of Verbal and Nonverbal Robot Cues on Perceived Confidence

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***Abstract*—With the wide variety of social robots being used today, it is important to understand how to use both verbal and nonverbal robot behaviours to communicate with users in human-robot interaction (HRI). In human-human interaction, people express self-confidence using verbal and nonverbal cues, and our perceptions of others’ confidence shapes the way we view them. However, it is not clear how a robot’s verbal and nonverbal confidence cues affect the human-robot interaction, or if one type of cue has a greater effect. In our work, we designed and implemented verbal and nonverbal confidence behaviours for a NAO robot, and conducted an online video observation study (n = 16) to compare the effects of the behaviours on perceptions of the robot. Our results show that participants viewed robots expressing a lack of confidence (verbal, nonverbal, or a combination of both) significantly less positively than robots showing total confidence, and we found minor evidence that verbal cues have a greater effect on perceived confidence than nonverbal cues.**

I. Introduction

Social robots are being used in a variety of settings around the world. There are various types of social robots, and the design of a social robot limits or enriches how it can communicate with users. For example, the android companion robot Grace can communicate using lifelike speech and facial movements [1] while the food service robot BellaBot communicates primarily with its electronic cartoon eyes [2]. With the diverse design of today’s social robots, it is important for robot designers to understand how to use both verbal and nonverbal robot behaviours in human-robot interaction (HRI). One important aspect of the human-human interaction that robot designers may wish to communicate through robot behaviours is confidence.

In human-human interaction, self-confidence is displayed using verbal and nonverbal behaviour cues. Verbal cues such as the speed and loudness of a response can influence perceptions of confidence [3], [4]. There is also evidence that nonverbal confidence cues can influence perceptions of others [5], [6]. For example, people are more likely to argue with referees when the referee uses unconfident body language [6], and politicians who deliver quality messages with high nonverbal confidence receive higher ratings [5]. People also rely on nonverbal confidence when verbal communication is not possible, such as when two drivers meet at an intersection and must communicate who should proceed first [7].

In the psychology literature, comparisons of verbal and nonverbal communication yielded varied results, with some experiments demonstrating that nonverbal communication has greater influence on perceptions of others [8], [9] and other studies finding no significant difference in effect [10]. Regarding perceived confidence, researchers have directly compared verbal and nonverbal confidence in human-human interaction. Walker [11] found that nonverbal confidence has a greater effect than verbal confidence. Relatedly, Tenney *et al.* [12] demonstrated that overconfidence is generally perceived more negatively when it is expressed verbally rather than nonverbally. However, little is known about how verbal confidence influences perceptions of robots, compared to nonverbal confidence.

In the HRI literature, comparisons of verbal and nonverbal robot behaviour generally show that nonverbal cues have greater effect on the interaction. Chidambaram *et al.* [13] found that people are more persuaded by a robot’s nonverbal cues than by its verbal cues. Further, Moon *et al.* [14] demonstrated that nonverbal cues can have greater influence than verbal cues, especially when the nonverbal cues express a negative emotion. However, HRI researchers have also found that participants in past studies misinterpreted or failed to notice nonverbal robot cues [15]–[17]. Thus, while there is evidence that both verbal and nonverbal robot cues can affect perceived confidence, it is not clear which behaviour type has greater effect on the human-robot interaction.

To our knowledge, there is no published research comparing the effects of verbal and nonverbal robot behaviours on perceived confidence in human-robot interaction. In our work, we conduct a video observation study to compare evaluations of verbal and nonverbal confidence cues in a humanoid NAO robot. Our findings contribute to the body of work on perceived confidence in HRI research, and more broadly to the literature on how verbal and nonverbal robot behaviours are perceived.

II. Background and Related Work

Comparisons of verbal and nonverbal displays of confidence have been performed previously in the psychology literature. Walker [11] conducted an experiment to investigate the influence of verbal and nonverbal cues on perceived confidence. Participants watched videos of an actress giving street directions and rated the expressed confidence of the performance. To portray confidence, the actress maintained strong eye contact and used decisive gestures. To portray lack of confidence, the actress averted her eye gaze and made indecisive hand gestures. The results demonstrate that nonverbal confidence cues have a much greater effect than the verbal confidence cues. Regarding perceptions of verbal and nonverbal confidence, Tenney *et al.* [12] found that the different displays of confidence may be perceived differently depending on the context of the interaction. People perceived overconfidence more negatively when it was expressed verbally and only perceived nonverbal overconfidence negatively when it was associated with an obviously false assertion.

In the HRI literature, the effects of nonverbal behaviour on perceived confidence are mixed. In some cases, the effects of nonverbal confidence in human-robot interaction match the findings from human-human interaction research. For example, Zeki [18] investigated the importance of nonverbal behaviours in a human-human classroom environment. Students reported they felt more motivated as a result of the teacher's nonverbal eye contact. Similarly, Karreman *et al.* [15] found that participants who received more eye contact from a museum guide robot paid more attention to the robot's dialogue. These results suggest that nonverbal robot confidence can have the same effect on the interaction as in human-human interaction, and that Walker's [11] results may be reproducible in HRI.

Regarding robot confidence and nonverbal behaviours, prior work in HRI has demonstrated that a robot's movements can influence perceptions of confidence [19]–[21]. Zhou *et al.* [20] manipulated the movements of a robot arm to investigate affects on perceived confidence. Pausing during a movement made the robot seem significantly less confident and high-speed movements made the robot seem significantly more confident. Aliasghari *et al.* [21] conducted an online survey study in which participants observed robot movements in a simulated iCub robot. Smooth, high-speed arm movements significantly affected perceptions of the robot's confidence compared to low-speed movements. Hesitant and spasmodic arm movements were found to lower perceived confidence of the robot. Similarly, Yamada *et al.* [19] demonstrated that participants can interpret high and low confidence from fast and slow robot movements.

Despite the evidence that nonverbal robot behaviours will have the greatest effect on perceived confidence, there is opposing evidence that people may misinterpret or fail to notice nonverbal robot cues and require additional explanations to make sense of nonverbal behaviours [15]–[17]. Han *et al.* [17] conducted a video observation study to determine if participants could interpret nonverbal robot cues without verbal explanations. Participants found the nonverbal behaviours unexpected and sought additional explanations for them. For example, when the robot shook its head to indicate it could not perform a task, participants reported being confused about the headshaking and misinterpreted it as disobedience. In addition, Stanton and Stevens [16] found that participants failed to notice manipulations of a robot's nonverbal eye gaze cues [16]. Participants also misinterpreted nonverbal gaze cues in a study conducted by Karreman *et al.* [15], suggesting that nonverbal gaze cues are interpreted differently in robots compared to people. Thus, it is not clear if comparisons of verbal and nonverbal confidence cues from the psychology literature can be indeed transferred to HRI.

In summary, we see that these mixed results suggest verbal and nonverbal confidence cues have different effects in human-robot interaction. However, it is not clear if verbal or nonverbal cues have greater effect on the interaction, or how the types of cues affect the interaction when they are combined or manipulated individually. To address these open questions in HRI, we directly compare the effects of verbal and nonverbal robot behaviours on perceived confidence by conducting a video observation experiment.

III. Research Question and Hypotheses

In this work, we investigate the research question of how a robot's verbal confidence cues affect perceived confidence, compared to nonverbal cues. In the psychology literature, there exists evidence that nonverbal confidence cues have greater effect than verbal cues [11]. Further, there is a large body of evidence to suggest that robots can use nonverbal cues to successfully communicate confidence or lack of confidence [19]–[21], despite opposing evidence that people may fail to notice or misinterpret nonverbal robot cues [15]–[17]. Based on these results, we developed the following hypotheses:

- **H1:** Nonverbal cues to signal confidence or lack of confidence will have a stronger affect on perceived confidence than verbal cues.
- **H2:** Robots using both verbal and nonverbal cues to signal confidence will be perceived as most confident.
- **H3:** Robots using both verbal and nonverbal cues to signal lack of confidence will be perceived as least confident.

IV. Method

A. Experimental Design

We conducted a video observation experiment in which participants evaluated videos of the humanoid robot NAO giving street directions to an imaginary coffee shop. The experiment had one independent variable: the behavioural cues used by the robot. In a within-participants design, each participant evaluated four possible combinations of the verbal behaviours (confident and unconfident) and nonverbal behaviours (confident and unconfident) we designed for the robot using four different videos we filmed. Thus, the experiment had four conditions:

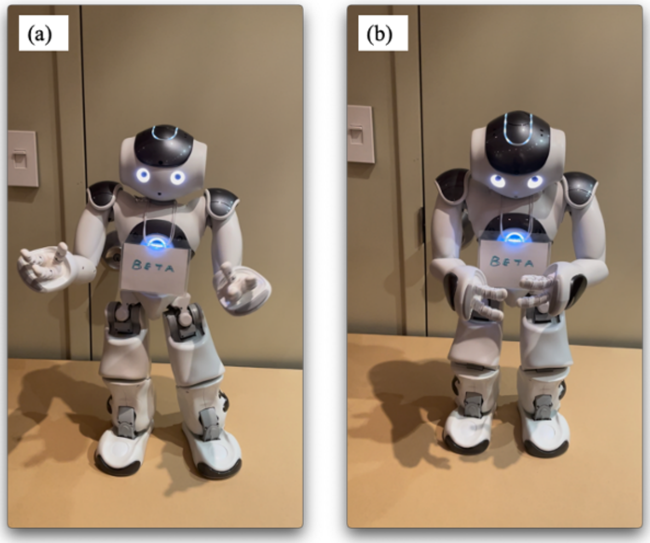

Fig. 1. Snapshots of the NAO robot displaying different body posture types: (a) expansive and confident versus (b) constricted and lacking confidence.

- *C1 (Totally Confident):* Robot demonstrated confident verbal and confident nonverbal behaviours.
- *C2 (Mixed Confidence I):* Robot demonstrated confident verbal and unconfident nonverbal behaviours.
- *C3 (Mixed Confidence II):* Robot demonstrated unconfident verbal and confident nonverbal behaviours.
- *C4 (Totally Unconfident):* Robot demonstrated unconfident verbal and unconfident nonverbal behaviours.

In all conditions, the robot repeated the same video script. The only manipulations between conditions were the manipulations to the robot's verbal and nonverbal behaviours shown in Table I. We used a Latin Square design to counterbalance effects of the order in which participants viewed the videos.

B. Design of the Robot Behaviours

We created both verbal and nonverbal behaviours for the NAO robot to communicate confidence or lack of confidence. To ground the design in the psychology literature, we transferred the behavioural manipulations used in past human-human interaction studies to the robot. Nonverbal behaviours used to signal confidence include looking at the conversational partner (eye contact) [11], [12], using decisive gestures [11], and holding an expansive body position [12]. Nonverbal behaviours used to signal lack of confidence include gaze aversion [11], [12], using indecisive gestures [11], and holding a constricted body posture [12]. Figure 1 shows snapshots of the robot using different body postures to express confidence or lack of confidence. Verbal behaviours used to communicate confidence include speaking loudly and quickly, with higher pitch and fewer pauses [11]. Verbal behaviours used to communicate lack of confidence include decreased loudness, variations in pitch, slower rate of speech, and long pauses [11]. Table I outlines the verbal and nonverbal manipulations used in our experiment to signal confidence or lack thereof.

TABLE I
OVERVIEW OF MANIPULATED VERBAL AND NONVERBAL ROBOT BEHAVIOURS.

	Verbal	Nonverbal
Confident	Loud voice, higher pitch, fewer pauses in speech, faster rate of speech	Eye contact, decisive gestures, expansive body posture
Unconfident	Quieter voice, variations in pitch, longer pauses in speech, slower rate of speech	Gaze aversion, indecisive gestures, constricted body posture

C. Design of the Robot Video

We filmed videos to demonstrate the robot behaviours to participants. In each video, the robot gives street directions to a pedestrian. We chose this scenario because it was used by Walker [11] to compare verbal and nonverbal confidence in human-human interaction. To ensure participants did not use the veracity of the directions in their evaluations, the robot gave directions to an imaginary location. Based on the previous studies, we constructed a neutral dialogue script for the robot that avoided confident or unconfident language. The script was:

- **Q:** Excuse me! Can you tell me how to get to the Mocha Magic Cafe from here please?
- **A:** Let me get your directions. O.K. The Cafe is located on Scott Street. If you go over the bridge and then turn left you'll be on a one way road. You'll see a sign there. You'll be O.K. if you follow the road.

In total, we recorded four different videos (one for each experimental condition) to demonstrate the four possible combinations of the verbal and nonverbal behaviours we created (see Table I). The videos ranged in length from between approximately 15 seconds (when the robot was speaking at a faster rate) and 30 seconds (when the robot was speaking more slowly and with pauses).

D. Experimental Procedure

The study was conducted entirely remotely using online survey and file sharing tools. Participants were invited to start the experiment through an online link to the participant information form and study instructions. Participants filled out a pre-experiment questionnaire to collect informal consent and relevant demographic data. For sensitive information such as gender identity, participants were given the option to skip the question. Participants were then asked to complete a list of step-by-step instructions which involved a series two-step tasks: watch a video of the robot and immediately fill out an online questionnaire to evaluate perceptions of the robot. Participants followed this process for each of the four videos (one for each of the four experimental conditions *C1*, *C2*, *C3*, and *C4*). Thus, each participant filled out a total of the five questionnaires: one demographic information questionnaire and four robot evaluation questionnaires (one for each video). The experiment lasted approximately 15 minutes.

E. Participants

We recruited 16 participants (close acquaintances and students at the University of Waterloo) using convenience sampling. The average age of participants was 30.75 years (SD = 12.03), with 10 male and 6 female participants. All participants were proficient in English, which was the language used to conduct the experiment. Participants varied in whether their post-secondary education related to a STEM field (50% STEM-related, 50% not) and their highest completed or current level of education (50% Bachelor's, 25% Master's, 12.5% Doctorate, 12.5% College credit). Participation was voluntary and participants did not receive remuneration for this preliminary study.

F. Measures

We used a pre-experiment questionnaire to collect demographic data about age, gender identity, level of education, and field of study. After each video, we had participants fill out a questionnaire to assess their perceptions of the robot. Participants were presented five-point Likert scales to measure perceived confidence, with high values indicating high agreement with the assessment item. In addition, participants were provided an open-ended question to explain their rating decision for overall perceived confidence. We also administered the Anthropomorphism, Likeability, and Perceived Intelligence scales from the Godspeed Questionnaire Series (GQS) [22] to measure additional perceptions of the robot.

V. Results

A. Quantitative Data Analysis

We used the SPSS Statistics software to perform one-way repeated measures ANOVAs and post-hoc analyses with a Bonferroni adjustment on the participants' responses to examine the effects of the four conditions (*C1*, *C2*, *C3*, and *C4*) on the quantitative measurements.

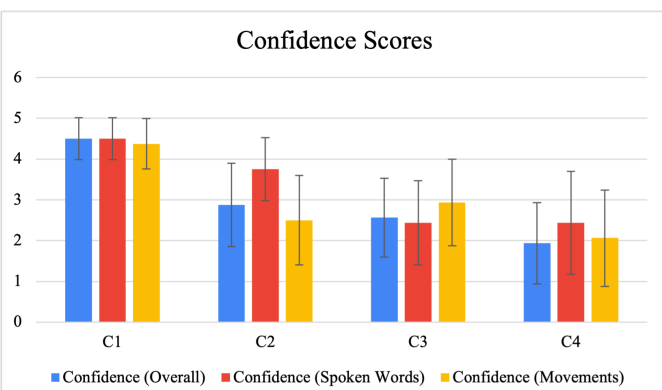

Fig. 2. Averages for confidence scores (robot's overall confidence, confidence of robot's spoken words, confidence of robot's movements) in each condition. Error bars indicate standard deviation. Highest possible score is 5 and lowest possible score is 1.

1) Perceived Confidence: We measured perceived confidence using the 5-point Likert item "The robot was confident" (see Figure 2 Overall scores). A one-way repeated measures ANOVA showed there was a statistically significant difference in perceived confidence between the four conditions ($F(2.786, 41.793) = 24.784$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed that participants in *C1* gave the robot a higher confidence rating compared to *C2* (mean difference = 1.625, 95% CI = [0.711, 2.539]), $p < 0.001$), *C3* (mean difference = 1.938, 95% CI = [0.999, 2.876], $p < 0.001$), and *C4* (mean difference = 2.563, 95% CI = [1.732, 3.393], $p < 0.001$). We also found a significant in difference in *C2* scores compared to *C4* scores (mean difference = 0.938, 95% CI = [0.085, 1.79], $p = 0.027$). No other significant effects of condition on perceived overall confidence were found.

In addition, we measured perceptions of the specific verbal and nonverbal cues using 5-point Likert items. Analysis of the item "The robot's spoken words were confident" (see Figure 2 Spoken Words scores) showed a significant difference between conditions ($F(2.286, 39.438) = 21.902$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed a significant difference between *C1* and *C2* (mean difference = 0.75, 95% CI = [0.1, 1.4], $p = 0.019$), *C1* and *C3* (mean difference = 2.063, 95% CI = [1.008, 3.117], $p < 0.001$), *C1* and *C4* (mean difference = 2.063, 95% CI = [0.938, 3.187], $p < 0.001$), *C2* and *C3* (mean difference = 1.313, 95% CI = [0.214, 2.411], $p = 0.015$) and *C2* and *C4* (mean difference = 1.313, 95% CI = [0.214, 2.411], $p = 0.015$). No other significant effects of condition on perceived confidence of the robot's spoken words were found.

Analysis of the item "The robot's movements were confident" (see Figure 2 Movements scores) showed a significant difference between conditions ($F(2.227, 33.411) = 17.384$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed a significant difference between *C1* and *C2* (mean difference = 1.875, 95% CI = [0.961, 2.789], $p < 0.001$), *C1* and *C3* (mean difference = 1.438, 95% CI = [0.655, 2.22], $p < 0.001$), and *C1* and *C4* (mean difference = 2.313, 95% CI = [1.324, 3.301], $p < 0.001$). No other significant effects of condition on perceived confidence of the robot's movements were found.

In summary, we found that participants rated the robot's confidence significantly higher in *C1* compared to the other conditions, and higher in *C2* compared to *C4*. Regarding perceived confidence of the robot's spoken words, participants in *C1* gave a significantly higher score compared to the other conditions, and *C2* gave a significantly higher score than *C3* and *C4*. Regarding perceived confidence of the robot's movements, participants in *C1* gave a significantly higher score compared to the other conditions. A key insight from the quantitative analysis is that participants in *C1* found the robot significantly more confident (with regard to overall confidence, confidence of spoken words, and confidence of movements) than participants in *C2*, *C3*, and *C4*.

2) Anthropomorphism: To measure perceived anthropomorphism, we used the GQS Anthropomorphism scale (see

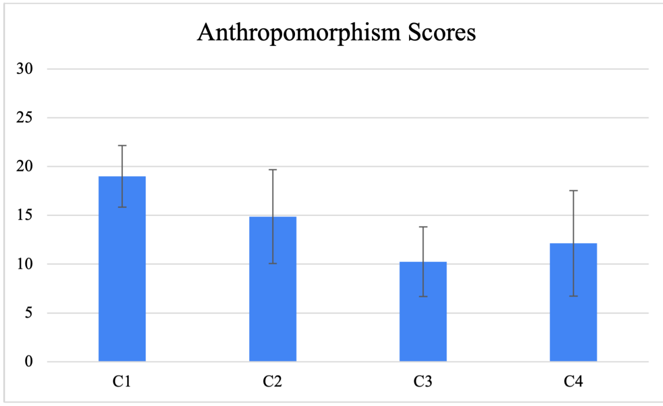

Fig. 3. Averages for anthropomorphism scores in each condition. Error bars indicate standard deviation. Highest possible score is 25 and lowest possible score is 5.

Figure 3). A one-way repeated measures ANOVA showed a significant difference between conditions ($F(2.383, 35.442) = 20.065$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed a significant difference between *C1* and *C2* (mean difference = 4.125, 95% CI = [1.116, 7.134], p = 0.005), *C1* and *C3* (mean difference = 8.75, 95% CI = [5.876, 11.624], $p < 0.001$), *C1* and *C4* (mean difference = 6.875, 95% CI = [2.547, 11.203], p = 0.001), and *C2* and *C3* (p = 0.015). No other significant effects of condition on perceived anthropomorphism were found. In summary, we found that participants rated the robot as significantly more anthropomorphic in *C1* compared to the other conditions. Analysis also showed a significantly higher score in *C2* compared to *C3*.

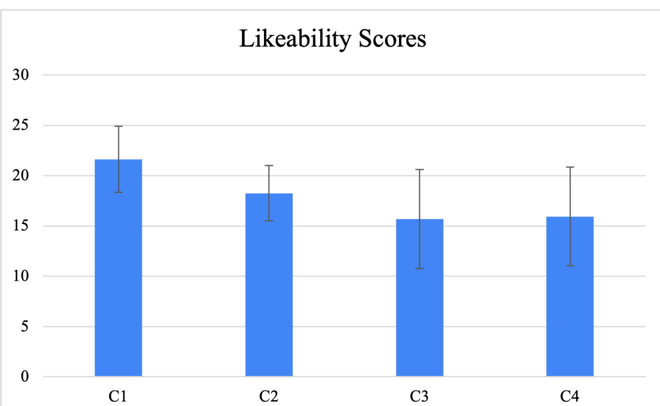

Fig. 4. Averages for likeability scores in each condition. Error bars indicate standard deviation. Highest possible score is 25 and lowest possible score is 5.

3) Likeability: To measure perceived likeability, we used the GQS Likeability scale (see Figure 4). A one-way repeated measures ANOVA showed a significant difference between conditions ($F(2.661, 39.916) = 8.669$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed that participants in *C1* gave the robot a significantly higher likeability score compared to *C2* (mean difference = 3.375, 95% CI = [0.097, 6.653], p = 0.042), *C3* (mean difference = 5.938, 95% CI = [1.693, 10.182], p = 0.004), and *C4* (mean difference = 5.688, 95% CI = [1.247, 10.128], p = 0.009). No other significant effects of condition on perceived likeability were found. In summary, we found that participants rated the robot as significantly more likeable in *C1*, compared to the other conditions.

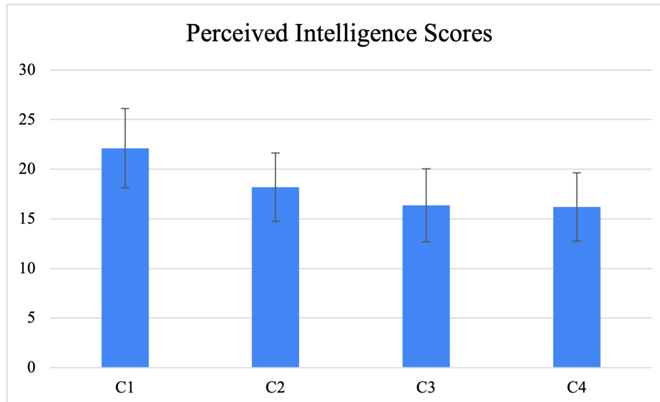

Fig. 5. Averages for perceived intelligence scores in each condition. Error bars indicate standard deviation. Highest possible score is 25 and lowest possible score is 5.

4) Perceived Intelligence: To measure perceived intelligence, we used the GQS Perceived Intelligence scale (see Figure 5). A one-way repeated measures ANOVA showed a significant difference between conditions ($F(2.146, 32.197) = 14.944$, $p < 0.001$). Post-hoc analysis with a Bonferroni adjustment showed that participants in *C1* gave the robot a higher intelligence score compared to *C2* (mean difference = 3.938, 95% CI = [0.538, 7.337], p = 0.019), *C3* (mean difference = 5.75, 95% CI = [2.372, 9.128], $p < 0.001$), and *C4* (mean difference = 5.938, 95% CI = [2.043, 9.832], p = 0.002). No other significant effects of condition on perceived intelligence were found. In summary, we found that participants rated the robot as significantly more intelligent in *C1*, compared to the other conditions.

B. Qualitative Data Analysis

We used the open-ended question "Why did you agree or disagree with the statement?" to ask participants to explain their reasoning regarding the robot's overall confidence rating (see Figure 2 Overall scores). We collected a total of 64 qualitative statements (one per condition, with all 16 participants evaluating four conditions), and analyzed them using an inductive thematic coding approach, in which categories are created based on the raw data. In particular, we aimed to gain insight into what behavioural cues participants used to form opinions about the robot's confidence. Participants' responses were classified systematically, and tended to fall into one or more of the following categories:

- *"Eye Gaze"*: statements referring to the robot's eye gaze or lack thereof. Observations about a tilt on the robot's head were also included, as they imply the direction of the robot's gaze. For example, the phrases "Looked directly at me” and “Kept looking down” were placed in this category.

- *“Body Language”*: explicit references to the robot’s body language. Comments on the robot’s movements and body posture were determined to fall within the broad category of body language, as they are physical behaviours used to communicate with others. For example, the phrases “Gesturing sheepishly” and “Closed body language” were placed in this category.
- *“Speech”*: statements about the way the robot uttered its dialogue, including observations about speed, volume, and tone of voice. For example, the phrases “Voice was soothing” and “Spoke in a smaller tone” were placed in this category.

Speech cues were highly discussed by participants, with 34 (53.13%) related statements. *Body Language* was discussed at an almost equal frequency, with 31 (48.44%) related statements. *Eye Gaze* was also noticeable, with 24 (37.5%) related statements. We found that gaze aversion was more remarkable to participants than strong eye contact, with 20 statements (31.25%) explicitly referring to the downward direction of the robot’s gaze or if the robot’s head was tilted down, and only 4 (6.25%) statements noting good eye contact from the robot.

VI. Discussion

We found a significant difference in perceived overall confidence ratings between only conditions *C1* and the other conditions, and between *C2* and *C4*. Given that a significant difference between *C2* and *C4* was found but no significant difference between *C3* and *C4* existed, our results do not support hypothesis **H1** which predicted that nonverbal confidence cues will have a greater effect than verbal confidence cues. To the contrary, our results provide preliminary evidence that verbal cues may have a greater effect. However, these findings do support **H2** which predicted that robots using both verbal and nonverbal cues to signal confidence will be perceived as most confident. In addition, because no significant difference in perceived overall confidence between *C3* and *C4* existed, our results do not support **H3** which predicted that robots using both verbal and nonverbal cues to signal lack of confidence will be perceived as least confident. In summary, we found evidence to support **H2**, but not **H1** or **H3**.

Our results showed that totally confident robots using both verbal and nonverbal cues to express confidence received significantly scores on all quantitative measures compared to robots that demonstrated unconfident behaviours. These results suggest that when robots use any type of behaviour (verbal, nonverbal, or a combination of both) to express lack of confidence, they will be perceived more negatively. One possible explanation for these findings is that unconfident robots violate our conception of robots as machines. Having low self-confidence is widely considered a uniquely human issue, so a robot expressing any lack of confidence may be perceived as damaged or malfunctioning. However, further scientific evidence is needed to conclude why people perceive unconfident robots more negatively than totally confident robots.

Further, we found that confidence ratings of the robot’s spoken words and movements were not always consistent with the robot’s programmed behaviours. Participants in *C2* rated the confidence of the robot’s spoken words significantly lower than in *C1* even though the robot used equally confident verbal behaviours in both conditions. Similarly, the robot used equally confident movements in *C1* and *C3*, but participants in *C1* rated the confidence of the robot’s movements significantly higher. These findings hint at a holistic relationship between expressed confidence and peoples’ perceptions of a robot’s spoken words and movements.

VII. Limitations and Future Work

Given the chance to reconduct this work in a formal capacity with approval from our institution’s Research Ethics Board, we would aim to recruit a much larger number of participants. Given the number of conditions and ease of running the online study with a crowd-sourcing tool such as Amazon Mechanical Turk, we recommend a minimum number of 80 participants (20 per condition). However, it may also be beneficial to conduct the experiment in-person with participants. Prior work in HRI has shown that results from virtual robot studies are not always replicable in real-world environments [23].

In addition, we lacked the data necessary to perform an in-depth qualitative analysis of participants’ explanations for the perceived confidence ratings they provided. We found it necessary to use a single open-ended question for this study due to the time cost of conducting interviews with each participant and analyzing the data. However, this led to a wide variation in responses, and the robot’s behaviours (verbal and nonverbal) were not discussed equally. In addition, it is likely that ordering effects influenced what behaviours were mentioned. For example, good eye contact may seem noteworthy only if the robot used poor eye contact in a previous video. Thus, we were only able to perform a high-level analysis of what behaviour was remarkable to participants. It is likely that greater insights could be gained from conducting an interview with participants, as researchers could guide participants to answer questions thoroughly and clarify ambiguous statements (for example, what a participant means when they use the broad term “assertive” and its related robot behaviours).

Further, our preliminary results showed that robots expressing a lack of confidence in any manner are perceived more negatively. Possible effects of unconfident robot behaviour on aspects of HRI that were not measured in our study (such as trust and acceptance) could be investigated in future work. For example, it would be interesting to investigate if people find an unconfident robot as trustworthy as a confident robot.

VIII. Conclusion

We conducted an online video observation study with a NAO robot to compare the effects of verbal and nonverbal robot confidence cues on perceived confidence. We discovered that totally confident robots using both verbal and nonverbal cues to express self-confidence were perceived significantly more positively than robots demonstrating any type of unconfident behaviour. We also found minor evidence suggesting that verbal cues have a greater effect on perceived confidence in HRI. Thus, while more research is needed, the results of our preliminary study provide insights on how to design confident and unconfident behaviours for social robots, as well as how verbal and nonverbal robot behaviours affect the human-robot interaction.

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References

[1] S. Jonas. "Meet grace, the humanoid robot offering companionship in a montreal nursing home," CBC. (), [Online]. Available: https://www.cbc.ca/news/canada/montreal/grace-humanoid-robot-montreal-seniors-study-1.6623292.

[2] M. Gillis. "Meet the cat-like robot now delivering orders at st. john's sushi restaurant," CBC. (), [Online]. Available: https://www.cbc.ca/news/canada/newfoundland-labrador/meet-the-cat-like-robot-now-delivering-orders-at-st-john-s-sushi-restaurant-1.5889841.

[3] C. E. Kimble and S. D. Seidel, "Vocal signs of confidence," *Journal of Nonverbal Behavior*, vol. 15, no. 2, pp. 99–105, Jun. 1991.

[4] X. Jiang and M. D. Pell, "The sound of confidence and doubt," *Speech Communication*, vol. 88, pp. 106–126, 2017.

[5] D. Dumitrescu, E. Gidengil, and D. Stolle, "Candidate confidence and electoral appeal: An experimental study of the effect of nonverbal confidence on voter evaluations," *Political Science Research and Methods*, vol. 3, no. 1, pp. 43–52, 2015. DOI: 10.1017/psrm.2014.16.

[6] P. Furley and G. Schweizer, "Nonverbal communication of confidence in soccer referees: An experimental test of darwin's leakage hypothesis," *Journal of Sport and Exercise Psychology*, vol. 38, no. 6, pp. 590–597, 2016.

[7] M. J. M. Satoshi Kitazaki, "Effects of non-verbal communication cues on decisions and confidence of drivers at an uncontrolled intersection," vol. 8, University of Iowa, Jun. 2015, pp. 113–119. DOI: 10.17077/drivingassessment.1559. [Online]. Available: https://pubs.lib.uiowa.edu/driving/article/id/28583/.

[8] C. S. Fichten, V. Tagalakis, D. Judd, J. Wright, and R. Amsel, "Verbal and nonverbal communication cues in daily conversations and dating," *The Journal of Social Psychology*, vol. 132, no. 6, pp. 751–769, 1992.

[9] A. Georgakopoulos and L. K. Guerrero, "Student perceptions of teachers' nonverbal and verbal communication: A comparison of best and worst professors across six cultures," *International Education Studies*, vol. 3, no. 2, pp. 3–16, 2010.

[10] W. Wang, "Verbal versus nonverbal communication in music performace instruction," *Contributions to Music Education*, vol. 28, no. 1, pp. 41–60, 2001, ISSN: 01904922. [Online]. Available: http://www.jstor.org/stable/24126965 (visited on 03/25/2024).

[11] M. B. Walker, "The relative importance of verbal and nonverbal cues in the expression of confidence," *Australian journal of psychology*, vol. 29, no. 1, pp. 45–57, 1977.

[12] E. R. Tenney, N. L. Meikle, D. Hunsaker, D. A. Moore, and C. Anderson, "Is overconfidence a social liability? The effect of verbal versus nonverbal expressions of confidence.," *Journal of Personality and Social Psychology*, vol. 116, no. 3, pp. 396–415, 2019.

[13] V. Chidambaram, Y.-H. Chiang, and B. Mutlu, "Designing persuasive robots: How robots might persuade people using vocal and nonverbal cues," in *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction*, ser. HRI '12, Boston, Massachusetts, USA: Association for Computing Machinery, 2012, pp. 293–300, ISBN: 9781450310635. DOI: 10.1145/2157689.2157798. [Online]. Available: https://doi.org/10.1145/2157689.2157798.

[14] B. J. Moon, J. Choi, and S. S. Kwak, ""'pretending to be okay in a sad voice": Social robot's usage of verbal and nonverbal cue combination and its effect on human empathy and behavior inducement," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2021, pp. 854–861. DOI: 10.1109/IROS51168.2021.9636709.

[15] D. E. Karreman, G. U. S. Bradford, E. M. A. G. van Dijk, M. Lohse, and V. Evers, "Picking favorites: The influence of robot eye-gaze on interactions with multiple users," in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2013, pp. 123–128. DOI: 10.1109/IROS.2013.6696342.

[16] C. Stanton and C. J. Stevens, "Robot pressure: The impact of robot eye gaze and lifelike bodily movements upon decision-making and trust," in *Social Robotics*, M. Beetz, B. Johnston, and M.-A. Williams, Eds., Cham: Springer International Publishing, 2014, pp. 330–339.

[17] Z. Han, E. Phillips, and H. A. Yanco, "The need for verbal robot explanations and how people would like a robot to explain itself," *J. Hum.-Robot Interact.*, vol. 10, no. 4, Sep. 2021. DOI: 10.1145/3469652. [Online]. Available: https://doi.org/10.1145/3469652.

[18] C. P. Zeki, "The importance of non-verbal communication in classroom management," *Procedia - Social and Behavioral Sciences*, vol. 1, no. 1, pp. 1443–1449, 2009.

[19] S. Yamada, K. Terada, K. Kobayashi, T. Komatsu, K. Funakoshi, and M. Nakano, "Expressing a robot's confidence with motion-based artificial subtle expressions," in *CHI '13 Extended Abstracts on Human Factors in Computing Systems*, ser. CHI EA '13, Paris, France: Association for Computing Machinery, 2013, pp. 1023–1028, ISBN: 9781450319522. DOI: 10.1145/2468356.2468539. [Online]. Available: https://doi.org/10.1145/2468356.2468539.

[20] A. Zhou, D. Hadfield-Menell, A. Nagabandi, and A. D. Dragan, "Expressive robot motion timing," in *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, ser. HRI '17, Vienna, Austria: Association for Computing Machinery, 2017, pp. 22–31, ISBN: 9781450343367. DOI: 10.1145/2909824.3020221. [Online]. Available: https://doi.org/10.1145/2909824.3020221.

[21] P. Aliasghari, M. Ghafurian, C. L. Nehaniv, and K. Dautenhahn, "Effects of gaze and arm motion kinesics on a humanoid's perceived confidence, eagerness to learn, and attention to the task in a teaching scenario," in *Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot Interaction*, ser. HRI '21, Boulder, CO, USA: Association for Computing Machinery, 2021, pp. 197–206, ISBN: 9781450382892. DOI: 10.1145/3434073.3444651. [Online]. Available: https://doi.org/10.1145/3434073.3444651.

[22] C. Bartneck, D. Kulić, E. Croft, and S. Zoghbi, "Measurement Instruments for the Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety of Robots," *International Journal of Social Robotics*, vol. 1, no. 1, pp. 71–81, Jan. 2009.

[23] S. Wallkötter, R. Stower, A. Kappas, and G. Castellano, "A robot by any other frame: Framing and behaviour influence mind perception in virtual but not real-world environments," in *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, ser. HRI '20, Cambridge, United Kingdom: Association for Computing Machinery, 2020, pp. 609–618, ISBN: 9781450367462. DOI: 10.1145/3319502.3374800. [Online]. Available: https://doi.org/10.1145/3319502.3374800.