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Social Robots as Decision-Making Companions: Exploring the Impact of Social Cues on Human Responses

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Making decisions, particularly ones fraught with ambiguity, inherently induces stress, which is a recognized contributor to long-term mental health issues. In high-stakes or uncertain environments, stress can significantly impair decision quality and well-being. Social robots offer a promising solution by potentially providing companionship and cognitive assistance in such scenarios. This study investigates the influence of verbal social cues used by social robots on human responses. In a laboratory setting, 60 participants interacted with the Alpha Mini robot, a programmable social agent, for 30 min. The robot offered advice using combinations of controlling language (high versus low) and social praise (absent versus present) in a between-subject design setup while playing a decision-making computer game. Post-interaction, social responses were measured using questionnaires. Results revealed strong, positive correlations between participants' enjoyment of interacting with the robot and their intention to use it again in the future, as well as their liking and trust in the robot's advice. These correlations were statistically significant ($p < 0.01$) and suggest that positive user experiences can translate into continued engagement. Positive responses were observed regardless of the specific social cues employed. To design effective human–robot interactions (HRI), multiple social cues should be integrated using high controlling language for clarity and direction paired with social praise to soften the tone in order to enhance trust, enjoyment, and effectiveness. Future work might enhance the current findings by integrating physiological data into the measures used to assess emotional responses to the robot and its cues. Additionally, expanding participant demographics and incorporating longitudinal studies could further validate and extend these results.

Keywords: Social robots; controlling language; social praise; decision-making game; social responses.

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1. Introduction

Imagine standing at a crossroads with an infinite number of paths stretching before you. Each path represents a possible choice, and each holds unknown, mysterious consequences. This very burden of choice can trigger anxiety and can be overwhelming, as the weight of finding the "right" path settles heavily upon our shoulders.

The process of decision-making, especially in complex or uncertain situations, can invoke significant mental stress as individuals struggle with evaluating various options, anticipating potential consequences, and prioritizing decisions.[1] This uncertainty can heighten stress levels as individuals feel pressured to choose the "best" option that aligns with their goals. Furthermore, decision-making involves weighing the pros and cons of different choices, triggering the fear of making mistakes and facing negative outcomes. This fear can activate the body's stress response, leading to physiological changes and amplifying stress.[2] Additionally, navigating conflicting information and worrying about potential errors may further intensify emotional tension and pressure on the mind during decision-making.

While stress is a natural response to challenging situations, its persistence or excess can detrimentally impact mental well-being. Several factors may contribute to stress, which may manifest as depression and ultimately, potentially lead to suicidal ideation.[3] Some individuals may feel stressed because they always strive for perfection.[4] Difficult situations like financial struggles can worsen these feelings, increasing the likelihood of depression or thoughts of self-harm. Additionally, individuals may experience stress due to a lack of social support, which can further fuel emotional distress.[5,6]

Earlier studies have shown that persuasive technology has the potential to provide companionship and offer advice in the decision-making process.[7,8] Persuasive technology refers to interactive systems or devices designed to shape human attitudes, choices, and actions through various motivational strategies, including social influence and defining objectives.[9] It leverages principles from psychology, behavioral economics, and human–computer interaction. Typically, this technology focuses on promoting beneficial changes, such as the development of health and wellness through trackers and apps.[10,11] The technology also focuses on enhancing education through adaptive learning platforms, as well as social and environmental change areas, such as recycling apps and charity donation platforms.[12–14]

Gamification, one of the persuasive strategies, is designed to be both entertaining and educational, occasionally leveraging the interactive nature of games to simulate real-world decision-making scenarios.[15,16] A number of studies highlight the educational benefits of serious games for healthcare professionals and students.[17,18] A fascinating example emerges from the development of a digital game for dental instruction during the COVID-19 pandemic, showcasing the feasibility of leveraging such extraordinary historical periods for serious game creation.[19,20] In the same vein, through the use of virtual dentistry simulations, participants make clinical decisions by clicking on relevant options as a form of training, simulating real-world scenarios without the associated risks.[21] Another example is "Digiworld", a developed virtual learning platform, where students use basic Python programming skills to progress through the game for programming education.[22]

Combining persuasive strategies, such as gamification, with persuasive technology — especially through social robots — offers a powerful way to improve the decision-making process. By incorporating gamification, tasks become more enjoyable and interactive, allowing social robots not only to make decision-making more engaging but also to offer a sense of companionship throughout the process. Users get involved, think about the results of their choices, and learn from them, all while feeling supported by the robot.[23] While feasible with virtual agents, physical agents elicit a stronger social presence effect albeit imposing additional affordances such as generally higher costs and the prerequisite of insight on features that may be exclusive to physical robots.[24] This approach helps people learn and improve their decision-making skills, encouraging them to make better choices.[25]

The success of social robots in providing companionship and cognitive assistance relies heavily on their ability to navigate the complexities of human interaction. Individuals react differently to the various persuasive strategies these robots employ; some find them appealing, while others are less so. When people engage positively with social robots, a sense of connection and trust develops, making them more likely to follow the robot's advice.[26] Similar to human-to-human communication, social cues are crucial in human–robot interactions (HRI), allowing them to exchange intentions and emotions.[27] These cues come in both verbal and non-verbal forms, including the tone of voice and body language, and ultimately shape the dynamics of the interaction.[28,29]

The challenge in HRI applications lies in determining which social cues should be implemented to ensure that interactions with social robots elicit positive responses, while also considering how people will react to the presence of social robots, particularly in the context of decision-making situations. The integration of social cues, like controlling language and social praise into social robots can augment their persuasive power and influence users' decision-making processes.[30,31] However, the misuse or misinterpretation of these social cues by social robots can lead to adverse outcomes, such as stress and distrust among users.[32] This emphasizes the critical need to establish trust and rapport between users and social robots, particularly in decision-making contexts where user trust is paramount.[33] A review by Xu *et al.* catalogued studies that involve the use of HRI under several aspects, with the most notable being the application of humanlike, intuitive, natural and spontaneous designs in addition to employing certain features such as language, movement, and facial cues which elicited the strongest impression of trust.[34]

This study aims to address the challenge of understanding the impact of social cues on people's responses to social robots in gamified decision-making situations by pursuing the following objectives:

(1) To establish fundamental social cues modality for positively perceived social robots (how the robots should talk in terms of controlling language and social praise) based on human responses after the interaction.

(2) To benchmark the correlations between social responses provided by participants after interacting with designated social robots.

This study uniquely explores the combined impact of two specific verbal social cues which are controlling language and social praise within gamified decision-making scenarios involving social robots. It is guided by Persuasive Technology Principles, particularly the Persuasive Systems Design model and Fogg's Behavior Model, which suggest that well-crafted cues act as effective triggers for behavior change.[35,36] Additionally, HRI theories like the Computers Are Social Actors paradigm and Social Presence Theory emphasize how verbal cues shape trust, empathy, and engagement in interactions with robots.[37,38] While previous research has examined social cues, persuasive technologies, and gamification separately, few studies have systematically investigated how the interplay of these verbal strategies influences human responses during complex decision-making with a physical robot.[39] The integration of these theories provides a robust framework for understanding how specific verbal cues can reduce stress, build trust, and enhance the effectiveness of decision support provided by social robots.

The scope of this research encompasses several key criteria. First, participants in the study are limited to individuals aged 18–25, with respect to legal capacity to make their own decisions according to Hall *et al.* who are the subject of the leading cause of death by suicide.[40] Second, this study evaluates the participants' social responses toward the robot, including perceptions of usefulness, attitude, intention, enjoyment, liking, belief, and reactance. Lastly, this research focuses on a singular type of robot, specifically the humanoid Alpha Mini robot. The general task of the interaction involves participants playing a computer game in which they must make decisions to escape from a large house which has eight rooms. Throughout this process, the robot acts as an advisor, guiding participants in selecting the most optimal choices to successfully navigate and exit each room. The Alpha Mini robot's capacity for integration with the larger system and its equipped features necessary for the effective execution of the experiment render it suitable. The following section will provide comprehensive elaborations regarding the game design, experimental setups, manipulations employed, and measurements utilized throughout the study.

2. Methods

This study was conducted in accordance with ethical guidelines and received approval from the International Islamic University Malaysia (IIUM) Research Ethics Committee: IREC 2022-044. Prior to their participation, all participants were provided informed consent forms, which outlined this study's objectives, procedures, duration, as well as any potential risks or discomforts associated with their participation. Signing the form declares each participant's consent to participate in this study.

2.1. *Participants and design*

A G-Power analysis based on similar prior research indicated that a minimum of 59 participants was necessary for the study. Sixty participants comprising 41 males and 19 females, aged 19–25 ($M = 22.17$, $\mathrm{SD} = 1.29$), took part in the experiment. The experimental sessions lasted approximately 60 min and participants were remunerated with MYR 15 in cash as a token of appreciation. Participants were recruited based on their responses to advertisements displayed outside the BioMechatronics laboratory, at the IIUM.

2.2. *Manipulations*

Participants were randomly allocated to four distinct groups, each subjected to a different social cue modality. These groups engaged with the robot in a between-subjects experimental design, employing a two-by-two factorial arrangement of social cues modality high versus low controlling language, and absent versus present social praise. The social cues were selected due to their notably effective effects that include but are not limited to: persuasive language elicits a higher rate of compliance and the perusal of social praises evokes a stronger sense of trusting beliefs toward the robot.[30,31] A between-subjects design was chosen to prevent carryover effects, learning, and fatigue by ensuring each participant experienced only one set of social cue conditions.[41] This approach enhances internal validity by isolating the influence of specific verbal cues on participant responses. Meanwhile, the two-by-two factorial design simultaneously examines the main effects of controlling language and social praise, as well as their interaction effects. This efficient structure provides comprehensive insights into how the interplay of these cues influences decision-making in HRI.

2.2.1. *Controlling language*

Highly controlling language exerts significant influence by presenting directives and limitations to the listener. It employs phrases and words that evoke authority, obligation, or insistence, aiming to compel compliance with the speaker's demands. Conversely, low controlling language fosters listener autonomy and choice. It avoids forceful phrases, opting for gentle suggestions or requests that promote cooperation. This approach empowers listeners by granting them agency and control over their decisions.[42] For instance, in a prompt used in this study, the robot uses high controlling language by saying, "As the most obvious choice, I am certain leather gloves would be the best option as leather gloves will offer the best grip on the zip line handle". In contrast, in the low-controlling language case, the robot says, "As another choice you could consider, I think leather gloves offer a good option as perhaps, it can grip on the zip line handle". Similarly, in Room 4, the robot in the high controlling language condition states, "I strongly believe that collecting 5 balls is a good balance of time to spend on diving and gathering the balls". In the low controlling language condition, the robot says, "I would consider that collecting 5 balls is a good balance of time to spend on diving and gathering the balls".

2.2.2. *Social praise*

In social settings, individuals often offer positive feedback or compliments, known as social praise. This can involve encouraging words, acknowledging achievements, expressing admiration, or showing gratitude for specific actions or behaviors.[43] Delivered verbally, through gestures, or written messages, social praise serves to reinforce desirable behaviors and strengthen social connections. While specific and contextually relevant praise offers numerous benefits, its effectiveness hinges on careful application, as social praise can diminish its impact and potentially breed skepticism or distrust.[43,44]

This study focuses on verbal social praise conveyed by the robot. For instance, in Room 4, the robot will complement the participants by saying, "By clearing this room, we should be halfway done through the rooms. You have excellent momentum". Conversely, in the absence of social praise, the robot will only state, "By clearing this room, we should be halfway done through the rooms". Other examples of social praises used were "You did a great job hanging on to that zipline", "You have very good aim, well done!" and "Your persistence is admirable".

2.3. *Social robot: Alpha mini*

The Alpha Mini robot as seen in Fig. 1 was designed by UBTECH. It is a humanoid robot intended for interaction with users across diverse environments, including

Fig. 1. Alpha Mini in idle mode.

educational and healthcare settings. It is known for its programmability and customizability, making it suitable for various applications. With its compact dimensions (H: 245 mm, W: 149 mm, T: 112 mm) and an expressive design, it facilitates engaging HRI, boasting 14 degrees of freedom. Equipped with dual-channel stereo speakers (0.8 W $\times$ 2), the Alpha Mini offers integrated features such as 4G capabilities, voice communication, and text-to-speech functionality. Additionally, it supports Python programming for executing text-to-speech commands and offers graphical programming options, aiding users in learning programming concepts. Supported by a Li-Polymer battery (3.85 V, 4060 mAh), it guarantees enduring performance, particularly for our case of conducting experiments. Regarding the social cues component, although the Alpha Mini robot can display expressions through its eyes and produce gestures, these behaviors were kept constant to minimize their influence when used in conjunction with the social cues chosen for this study.

2.4. *Procedure*

Figure 2 depicts the experiment flowchart. The experimenter introduced himself and provided a consent form with details about the study. Participants were instructed to carefully read the form and sign it upon participation agreement. Next,

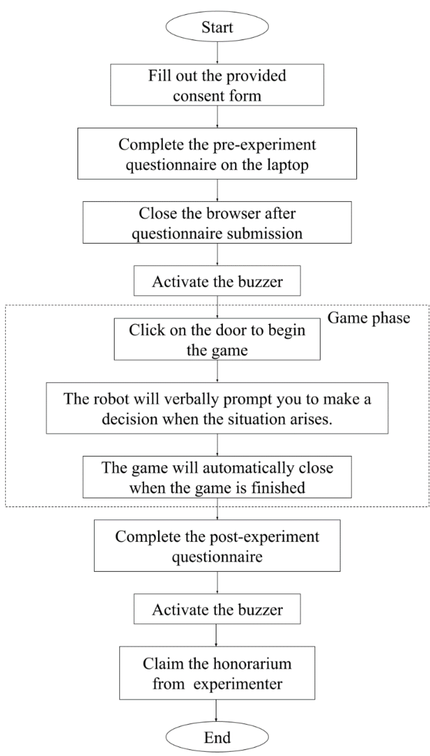

Fig. 2. Flow of the experiment.

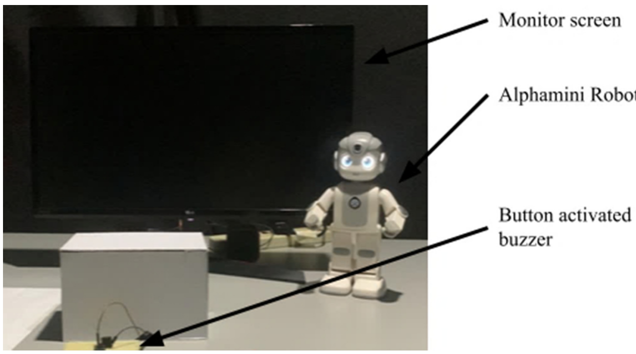

Fig. 3. Participants' view during the experiment.

participants were instructed to sit comfortably and view the monitor. The setup included a mouse, keyboard, Alpha Mini robot, and game monitor. A black cloth was used to partition off the room to minimize distractions during the experimental sessions as shown in Fig. 3. Afterwards, the experimenter left the room for privacy. Participants completed a Google Form questionnaire on the monitor to measure their baseline stress level. They would then use the buzzer to call the experimenter back after submitting the Google Form questionnaire. Upon returning, the experimenter demonstrated the game by showing the basic concept of the game. Participants could ask questions before the experimenter launched the full game. Before starting, the experimenter explained that the game would automatically close, and a second questionnaire would appear. Participants were instructed to use the buzzer for any issues or after submitting the questionnaire. This second questionnaire assessed the participants' post-experiment stress level and their responses to the robot. The game phase then begins.

Following the experimenter's departure, the Alpha Mini robot initiated the experiment by introducing itself and outlining the game's theme and ultimate mission. Participants proceeded with gameplay, assisted by the robot in making the 'best' decisions. Upon completion of the eight missions, before concluding the experiment, the Alpha Mini robot reminds the participants to fill out and submit the second Google Forms questionnaire. Participants would then signal their completion by pressing the buzzer. The experimenter would then express their gratitude, address any remaining questions during a brief debriefing, and provide an RM15 honorarium for their participation.

2.5. *Game design*

Participants in an escape room-themed study were presented with eight distinct missions, each represented by a virtual room. The experiment employed the Alpha Mini robot to guide participants and influence their decision-making throughout the game. The stress component was induced through two effects: urgency as stated by

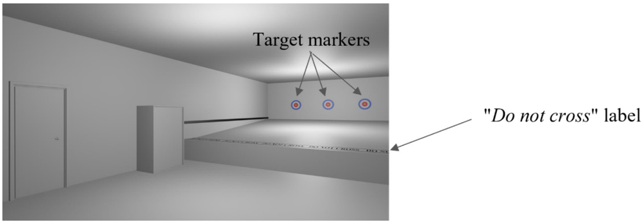

Fig. 4. Overview of tossing room.

the Alpha Mini robot to complete the tasks as quickly as possible and the suggestions of alternative options. Upon entering each room, participants encountered an introductory phase. During this phase, the robot introduced the specific mission objective and potential challenges. Figure 4 presents an example of the graphical user interface (GUI) encountered by participants during the initial selection phase within Room 2: Tossing room mission. To overcome the challenge presented in the Tossing room and unlock the door to the next room, participants encountered three target markers on the wall at the far end and a line across the ledge labeled "Do not cross". The objective was to hit three target markers to proceed. To aid this task, participants were presented with several throwable items stored in a nearby cabinet. They were then asked to choose the item they believed would be most effective in hitting the targets and opening the door to the next room. In general, after the introductory phase, the game presented participants with 10 options as shown in Fig. 5 and the participants were then required to make an initial selection to complete the mission.

This was followed by a persuasive phase, where the robot attempted to persuade an alternative option from the participant's initial decision regarding how to approach the challenge. Social cues, varying in controlling language and social praise, were incorporated into this phase to manipulate participant perception and decision-making. The persuasive phase is crucial in inducing stressful environments. Following the persuasive phase, participants were presented with the option to revise

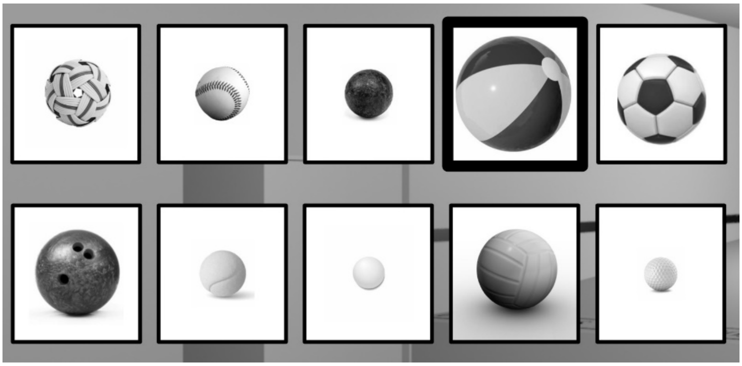

Fig. 5. Options given for Room 2 with the beachball option being highlighted as the cursor hovers over it.

their initial selection based on the robot's suggestion, maintain their original choice, or choose an entirely different option. Notably, there were no predetermined correct or incorrect answers. The game-robot integration was programmed in such a way that an alternative option would be suggested regardless of whichever option the participant picked initially. Finally, a resolution phase concluded in each room. Based on the participant's final selection, the robot offered feedback by expressing social praise (or not) based on the settings before facilitating progression to the next room.

Throughout the game, participants encountered a variety of challenges requiring diverse choices. Room 1 involved selecting gloves for a zipline crossing, while Room 3 presented a choice between boxing gloves and a baseball bat. The remaining rooms (tossing, punching bag, diving, firewall, running, balancing, and see-saw) offered similarly distinct decision points.

2.6. *Measures*

Stress responses of participants were assessed twice: pre-experiment and post-experiment. The State-Trait Anxiety Inventory (STAI) and psychological reactance questions were used to measure general stress levels using 10 items on a 4-point Likert scale in the pre-experiment questionnaire as shown in Table 1.[45,46] Each item consisted of a statement regarding negative emotions, requiring participants to rate their agreement on a scale from 1 (strongly disagree) to 4 (strongly agree). These items encompass feelings such as upset, uncomfortable, indecisive, jittery, confusion, and worry from the STAI, as well as anger, annoyance, aggravation, and irritation from reactance, both before and after the interaction.

For the post-experiment questionnaires, in addition to the STAI and reactance, other questions adapted from a previous study were used to assess the participants' responses.[7] This questionnaire measured perceived usefulness, ease of use, attitude, liking, intention, enjoyment, and belief toward the social robot. All statements, except for reactance, were rated on a 7-point Likert scale (1 = strongly agree, 7 = most agree). Additionally, reactance was also assessed using an item measuring negative cognition through word frequency.[47]

2.7. *Analysis*

Three main methods of analysis were applied to the collected data: Reliability, statistically significant effects, and correlations. Reliability analysis was conducted

Table 1. STAI items.

Number	Item
1	I feel upset
2	I feel uncomfortable
3	I feel indecisive (hesitant)
4	I feel jittery (nervous)
5	I feel confused
6	I feel worried

from the assessment of Cronbach's α. Statistically significant results were attained through the Analysis of Variance (ANOVA) statistical method. Correlations were assessed through the Pearson Correlation Coefficient.

3. Results and Discussion

Based on the collected data, a reliability analysis was conducted on STAI and social response items. Subsequently, ANOVA was conducted for each of the social response items each grouped by social response and individual items. All participants completed the experiments.

3.1. *Preliminary analysis*

ANOVA was conducted on the effects of age and gender on the outcomes of this study. No statistically significant influence was observed based on the age and gender of the participants.

3.2. *Reliability analysis*

Since the average value was mostly above 0.7, further analysis was conducted as they fell within acceptable values. Table 2 displays the pre-experiment and post-experiment Cronbach's α scores for STAI and reactance measures.

The Cronbach's α values for both STAI and reactance in pre-experiments and post-experiments were within the acceptable range of reliability, in the range of 0.6 to 0.8.[7,48] To create a composite response named "Stress" by combining the STAI and reactance scales, Cronbach's α analysis was conducted. This procedure ensures that both measures exhibit internal consistency and effectively capture the intended constructs, thereby enhancing the validity of their combination into a unified variable. The results indicated that the internal consistency reliability of both pre-experiment and post-experiment measures remained intact even after their combination, with Cronbach's α values of 0.814 and 0.795 with $N = 10$, respectively. Proceeding to assess other social responses recorded in post-questionnaires, the same reliability tests were conducted by calculating Cronbach's α for each response individually. Details are shown in Table 3.

The values of Cronbach's α suggest that the responses are reliably measuring the intended constructs, with higher values indicating stronger internal consistency

Table 2. Reliability analysis for STAI items.

	Experiment			
	Pre-experiment		Post-experiment	
Measures	STAI	Reactance	STAI	Reactance
Cronbach's α	0.847	0.916	0.775	0.949
N	6	4	6	4

Table 3. Reliability analysis for each social response used in post-questionnaires.

Response	Cronbach's α	N
Usefulness	0.68	5
Ease	0.718	4
Attitude	0.732	4
Intentions	0.882	4
Enjoyment	0.995	4
Liking	0.922	13
Belief	0.895	7

among the items. Overall, the internal consistency of the questionnaire is acceptable. Most α values fall within the 0.7–0.9 range, which is generally considered reliable for social science research.[49]

3.3. *Influence of social cues on social responses*

Statistical analysis was conducted on the social responses using ANOVA. In this analysis, the use of social cues, including controlling language and social praise, served as independent variables, while the social responses were considered dependent variables. Intriguingly, the effects of social cues on participants' responses manifested at the level of individual questionnaire items rather than across the entire response set. These effects can be categorized as main effects (independent influence of controlling language or social praise) and interaction effects (combined influence of both cues). An analysis conducted on the perceived stress between the pre-experiment and post-experiment across all four groups yielded no significant results. However, there was a statistically significant reduction in stress experienced by all participants. $F(1, 112) = 5.04$, $p = 0.03$, partial $\eta^2 = 0.041$ between the start ($M = 1.49$, $\text{SD} = 0.41$) and the end ($M = 1.33$, $\text{SD} = 0.38$) of the experiment. The analysis revealed no significant main or interaction effects of controlling language and social praise on participants' social responses. Separate ANOVAs were conducted for each item to examine these effects on individual responses. Unspecified items in each response showed insignificant statistical differences. Significant findings were then categorized based on the type of social cue effect. Notably, the "ease" social response category did not reveal any significant differences across the four experimental groups.

3.3.1. *Usefulness*

The perceived usefulness of social robots is known to vary based on factors like functionality, aesthetics, and applications.[50] This study identified several significant effects within our experimental parameters that influenced participants' perceptions of the robot's usefulness.

First, a significant interaction effect ($F(1, 56) = 4.89$, $p = 0.03$, partial $\eta^2 = 0.08$) was observed between controlling language and social praise on decision-making confidence. Participants' felt more confidence in choosing their decisions ($M = 5.93$, $\mathrm{SD} = 0.884$) when the robot employed low controlling language without social praise. Conversely, high controlling language with social praise ($M = 5.19$, $\mathrm{SD} = 1.642$) resulted in decreased confidence. Participants reported higher confidence with low controlling language and no social praise, possibly because low controlling language allows increased self-agency and control in their decisions. Social praise in this condition might have come across as patronizing or unnecessary, sapping the participants' confidence.

Second, in terms of decision speed and simplification, the participants perceived a significant main effect ($F(1, 56) = 5.63$, $p = 0.02$, partial $\eta^2 = 0.09$) on their ability to decide quickly and easily among options when using the robot as an advisor. High controlling language ($M = 4.87$, $\mathrm{SD} = 1.43$) led to a perception of faster and easier decision-making compared to low controlling language ($M = 4.24$, $\mathrm{SD} = 1.56$) in line with the findings of a prior study.[51] The direct nature of the prompt may have given clear and direct statements that minimized uncertainty. In contrast, the ambiguity due to the phrasing of the low controlling prompt may have bred doubt, hence delaying the decision-making process.

Finally, in terms of understanding options, both interaction and main effects impacted participants' understanding of the suggested options. A significant interaction effect ($F(1, 56) = 3.72$, $p = 0.06$, partial $\eta^2 = 0.06$) revealed that participants felt better informed with low controlling language and social praise ($M = 6.00$, $\mathrm{SD} = 0.91$) compared to high controlling language with social praise ($M = 4.40$, $\mathrm{SD} = 1.50$). Additionally, a significant main effect ($F(1, 56) = 8.30$, $p = 0.006$, partial $\eta^2 = 0.13$) indicated that participants generally felt better informed with low-controlling language ($M = 5.83$, $\mathrm{SD} = 1.10$) compared to high-controlling language ($M = 4.87$, $\mathrm{SD} = 1.43$). This particular modality likely benefitted from the combination of encouragement due to the social praise with the accommodating delivery of the low controlling language social cues.

3.3.2. *Attitude*

An interaction effect between controlling language and social praise on participants' belief in the robot's benefit for improving decisions approached significance of ($F(1, 56) = 2.35$, $p = 0.13$, partial $\eta^2 = 0.04$). While not statistically conclusive, the results suggest a trend where participants perceived the robot as most beneficial ($M = 6.25$, $\mathrm{SD} = 0.78$) when it used high-controlling language without social praise. This outcome aligns with a prior study indicating that users might perceive tools as more effective when presented with a functional approach, potentially due to a reduced focus on persuasion compared to situations with social praise.[52]

3.3.3. *Belief*

A notable primary effect of language control on participants' perceptions of the ethical behavior of a robot was evident ($F(1, 56) = 2.93$, $p = 0.09$, partial $\eta^2 = 0.05$).

Participants perceived the robotic advisor as more ethical when employing high-controlling language ($M = 6.14$, SD $= 1.09$) compared to low-controlling language ($M = 5.61$ and SD $= 1.23$) which coincides with findings from previous work.[53] Typically, one would generally assume to feel more constrained when subjected to high-controlling language. This finding could be attributed to the manner in which the high-controlling language was delivered.

Furthermore, an interaction effect was observed concerning participants' inclination to adhere to the robot's advice ($F(1, 56) = 2.33$, $p = 0.13$, partial $\eta^2 = 0.04$). Participants indicated a greater likelihood of compliance when the robot employed high-controlling language with social praise ($M = 4.88$, SD $= 1.2$), whereas compliance was perceived to be least likely when the robot employed high-controlling language without social praise ($M = 4.2$, SD $= 1.21$). These findings align with a study that utilized a perfunctory social cue modality and resonates with the findings regarding the effects of social cues on trust beliefs.[54,55] Specifically, the perusal of the social praise meant the difference in the effect of compliance, likely due to making the instruction more agreeable.

3.3.4. *Enjoyment*

A significant main effect of social praise on participants' enjoyment of utilizing the robot was observed ($F(1, 56) = 3.02$, $p = 0.09$, partial $\eta^2 = 0.05$). Participants reported a more enjoyable experience when the robotic advisor incorporated social praise ($M = 6.48$, SD $= 0.74$) compared to when it did not use social praise language ($M = 6.06$, SD $= 1.24$). The presence of social praise cues reinforces the specific response of finding the use of the robot to be entertaining.[56] The presence of social praise may have alleviated the cold and mundane experience of interacting with a robot.

3.3.5. *Intent*

A significant main effect of controlling language was observed on participants' likelihood to express favorable sentiments about the robot ($F(1, 56) = 2.39$, $p = 0.13$, partial $\eta^2 = 0.041$). Participants were more inclined to express favorable remarks when the robot employed high controlling language ($M = 5.74$, SD $= 9.10$) compared to when it used low controlling language ($M = 5.34$, SD $= 1.08$), in line with the findings of another study.[57] The conveyance of the high controlling language may have instilled a more professional and competent impression of the robot, advocating for more positive responses.

Similarly, there was a significant main effect of social praise on participants' certainty regarding their willingness to use the robot ($F(1, 56) = 3.3$, $p = 0.08$, partial $\eta^2 = 0.06$). Participants expressed greater certainty in their intention to use the robot when it utilized social praise ($M = 5.26$, SD $= 1.309$) compared to when it did not incorporate social praise language ($M = 4.59$, SD $= 1.427$). The friendlier and natural effect due to the inclusion of social praise may be the most likely factor in this attribution.

3.3.6. *Liking*

A significant main effect of controlling language was observed on participants' perception of the robot's honesty ($F(1, 56) = 2.23$, $p = 0.15$, partial $\eta^2 = 0.01$). Participants perceived the robotic advisor as more honest when employing high-controlling language ($M = 6.32$, SD $= 0.83$) compared to low-controlling language ($M = 5.9$, SD $= 1.32$). Additionally, participants generally perceived the robot as more sincere ($F(1, 56) = 6.33$, $p = 0.15$, partial $\eta^2 = 0.10$), particularly when it used high-controlling language ($M = 5.97$, SD $= 1.048$) compared to low-controlling language ($M = 4.97$, SD $= 1.88$). The straightforward statement from the applied high-controlling language social cue may elicit a strong expression of honesty, whereas the low-controlling language social cue may appear as evasive.

Furthermore, a significant main effect of social praise was observed on participants' perception of the robot's friendliness ($F(1, 56) = 2.29$, $p = 0.14$, partial $\eta^2 = 0.04$). Participants perceived the robotic advisor as more friendly when it provided social praise ($M = 5.90$, SD $= 1.30$) compared to when it did not use social praise ($M = 5.48$, SD $= 1.77$). This finding is consistent with another study that noted that properties exhibited by social cues are perceived as pleasant.[58] The participants likely found the use of social praise as more pleasant and easier to conform to as opposed to without.

Additionally, there was a significant main effect of social praise on participants' perception of the robot's confidence ($F(1, 56) = 2.45$, $p = 0.12$, partial $\eta^2 = 0.04$). Participants perceived the robotic advisor as more confident when it did not use social praise ($M = 6.48$, SD $= 0.74$) compared to when it used social praise language ($M = 6.06$, SD $= 1.24$). The robot may have exuded a stronger sense of confidence as it delivered statements without the reliance on polite remarks.

3.3.7. *Reactance*

A significant main effect of social praise was observed on participants' feelings of anger toward the robot ($F(1, 56) = 3.40$, $p = 0.06$, partial $\eta^2 = 0.07$). Participants reported higher levels of anger toward the robotic advisor when it used high-controlling language ($M = 1.79$, SD $= 1.05$) compared to when it used low-controlling language ($M = 1.39$, SD $= 0.56$), a finding consistent with a prior study despite differences in the medium of robot expression.[59] The manner in which the robot converses with the participant presents itself as an overbearing authoritative entity, resulting in a negative emotional response. Similarly, participants experienced increased irritation toward the robot ($F(1, 56) = 6.00$, $p = 0.02$, partial $\eta^2 = 0.11$). They felt more irritated by the robotic advisor when it used high-controlling language ($M = 2.48$, SD $= 1.27$) compared to when it used low-controlling language ($M = 1.87$, SD $= 0.85$). This was possibly due to the robot conversing using callously phrased statements.

A simple frequency analysis based on the questionnaire was conducted to ascertain its general effects according to the distribution of means across all participants.

The frequency analysis indicates a significant impact of social praise, evident as both a main effect and an interaction effect on participants. Additionally, high-controlling language was frequently associated with instances where positive social responses were perceived. This suggests that the combined use of high-controlling language with social praise had a notable effect, serving as both a main effect and a component of interaction effects on participants.

In sum, the key findings of the interaction effect and the main effect of each independent variable on the dedicated dependent variables and their items can be summarized as in Tables 4–6. This analysis yielded critical information that is invaluable when consolidating the choice of applied social cues to generate the most desired effects.

3.4. *Correlation*

Pearson correlation analysis was employed to evaluate the social responses of participants following interactions with the social robot, with the findings presented in Table 7. To summarize the findings depicted in Table 7, Fig. 6 illustrates the significant correlations among the social responses. Through the visualization in Fig. 6,

Table 4. Mean values of controlling language as the main effect. Underlined values highlight referred social response means of items for each social cue mode.

		Independent variable means	
Variable	Question	High	Low
Usefulness	Participants can decide more quickly and easily the options I want to choose than without using this robotic advisor	$\underline{4.87}$	4.24
	Participants are better informed about the suggested options	4.87	$\underline{5.83}$
Intentions	Participants would say something favorable about this robotic advisor	$\underline{5.74}$	5.34
Liking	Participants believe that this robotic advisor was sincere	$\underline{5.97}$	4.97
	Participants believe that this robotic advisor was honest	$\underline{6.32}$	5.9
Belief	Participants believe that this robotic advisor behaves in an ethical manner	5.61	$\underline{6.14}$

Table 5. Mean values of the presence of social praise as the main effect. Underlined values highlight referred social response means of items for each social cue mode.

		Independent variable means	
Variable	Question	Present	Absent
Usefulness	Participants believe that they would certainly use it	$\underline{5.26}$	4.59
Enjoy	Participants would find using this robotic advisor to be fun	$\underline{5.94}$	5.31
Liking	Participants believe that this robotic advisor was confident	6.06	$\underline{6.48}$
	Participants believe that this robotic advisor was friendly	$\underline{5.90}$	5.34
Reactance	Participants feel irritated toward this robotic advisor	$\underline{1.87}$	2.48
	Participants feel angry toward this robotic advisor	$\underline{1.39}$	1.79

Table 6. Mean values of the interaction effect of high or low controlling language with the presence of social praise. Underlined values highlight referred social response means of items for each social cue modes.

		Means			
		High controlling language		Low controlling language	
Variable	Question	Value	Social praise presence	Value	Social praise presence
Usefulness	Participants are better informed about the suggested options	<u>5.33</u> versus 4.44	Absent	<u>6.00</u> versus 5.64	Present
	Participants can decide more quickly and more easily whether they want to choose the suggested option or not	<u>5.60</u> versus 4.81	Absent	<u>5.40</u> versus 4.64	Present
	Participants can better decide whether I want to choose the suggested option or not	<u>5.93</u> versus 5.19	Absent	<u>5.93</u> versus 5.29	Present
Attitude	Participants believe that this robotic advisor is beneficial in improving their decision	<u>6.25</u> versus 5.87	Present	<u>6.14</u> versus 5.93	Absent
Belief	Participants will follow the advice that this robotic advisor gives them	<u>4.88</u> versus 4.2	Present	<u>4.57</u> versus 4.33	Absent

Table 7. Pearson correlation statistics of the responses.

Response		Usefulness	Ease	Attitude	Intent	Enjoyment	Liking	Beliefs
Ease	Pearson Correlation	0.101						
	Significance	0.443						
Attitude	Pearson Correlation	0.063	0.513^{1}					
	Significance	0.631	<0.001					
Intent	Pearson Correlation	−0.185	0.378^{1}	0.680^{1}				
	Significance	0.157	0.003	<0.001				
Enjoyment	Pearson Correlation	−0.079	0.264^{2}	0.452^{1}	0.751^{1}			
	Significance	0.548	0.042	<0.001	<0.001			
Liking	Pearson Correlation	−0.107	0.474^{1}	0.515^{1}	0.525^{1}	0.621^{1}		
	Significance	0.415	<0.001	<0.001	<0.001	<0.001		
Belief	Pearson Correlation	−0.061	0.590^{1}	0.606^{1}	0.685^{1}	0.652^{1}	0.778^{1}	
	Significance	0.644	<0.001	<0.001	<0.001	<0.001	<0.001	
Reactance	Pearson Correlation	0.176	-0.438^{1}	−0.208	-0.325^{2}	−0.247	-0.332^{1}	-0.444^{1}
	Significance	0.179	<0.001	0.111	0.011	0.057	0.01	<0.001

Notes: 2 = Correlation is significant at the 0.01 level (2-tailed); 1 = Correlation is significant at the 0.05 level (2-tailed).

indicated by lines of varying thickness representing the strength of correlations, several observations can be made. Solid lines denote significant positive correlations, while dotted lines indicate significant negative correlations, with the absence of lines representing insignificant correlations.

Notably, a robust correlation exists between intention and enjoyment of using the robot with $r(58) = 0.08$, $p = 0.001$, suggesting that individuals who derive enjoyment from their interaction with the robot are more likely to express intentions to use it again in the future. Participants enjoyed the interaction to a degree that they

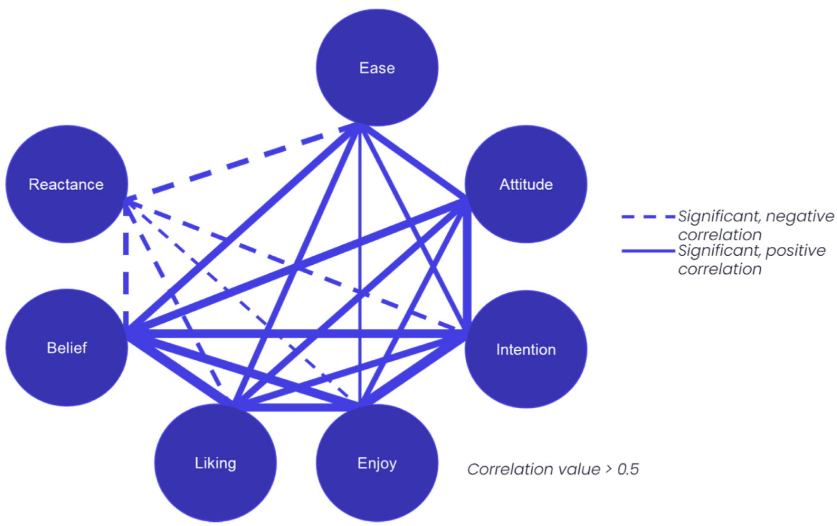

Fig. 6. Correlation test outcomes.

would consider employing its future use. Practical applications based on this correlation should capitalize on the use of features that make the experience more fun and rewarding and incentivize continued use. Positive correlations were also evident across various other responses, consistent with the findings of a previously referenced study.[7] Moreover, correlations among ease and enjoyment, ease and attitude, and attitude and intentions align with technology acceptance models proposed by prior studies.[59,60]

3.5. *Social cues design and implications*

Based on the findings from the statistical analysis of social responses, particularly focusing on the effects of controlling language and social praise on participants' perceptions, several design implications can be drawn to ensure that people perceive robots positively.

Notably, a significant effect of reactance responses was observed when the social cue of social praise was applied. One may conclude that negative cognitions may be mitigated or nullified when both cues are applied in tandem. Some considerations for future iterations include the omission of social praise as a social cue to avoid its potentially inherent negative effects or to ensure that it is applied in conjunction with the controlling language social cue.

Unlike the manipulation of high or low-controlling language within the spectrum of social cue modalities, the presence of social praise itself serves as a distinctive cue. Consequently, in certain social modalities, the mere presence of social praise denotes the utilization of multiple social cues. Drawing insights from the results, several observations emerge. Primarily, participants demonstrated heightened reactions in terms of reactance, anger, and irritation toward the social robot when only one social cue was present. Conversely, when both social cues were simultaneously present, participants indicated a shared intention to use the robot, perceived the interaction as enjoyable, and regarded the robot as friendly. Considering reactance as a response indicative of aversion toward the robot, it can be inferred that the utilization of multiple social cues elicits a generally more positive response from participants. Hence, the findings corroborate prior research outcomes pertaining to the theory of employing multiple social cues for favorable responses.[61,62] A more concrete affirmation of this result may be obtained by applying less dissimilar social cue modalities to minimize the inherent effects of each social cue on the interaction.

4. Conclusion

This study aimed to quantify how specific social cues which are controlling language and social praise affect users' responses to social robots in gamified decision-making scenarios. Focusing on a cohort aged 18–25 interacting with the humanoid Alpha Mini robot, the investigation measured perceptions of usefulness, attitude, intention, enjoyment, liking, belief, and reactance under controlled variations of language and praise parameters. While ANOVA identified detailed effects on metrics such as decision-making confidence, speed, comprehension, and stress levels, correlation analysis established a robust link between intention and enjoyment of robot interaction. The findings indicate that the integration of multiple social cues, particularly the combination of social praise with controlling language, can enhance user experience by mitigating negative reactions and promoting trust and engagement.

Identified areas for improvement include enhancing the robot's speech delivery to achieve a more natural flow and implementing more advanced interactive physical behaviors to increase engagement. The technical insights derived from this research can guide the design of optimized social agents with streamlined social features for specific applications. Future work should investigate additional social cue modalities, broaden participant demographics, and assess the long-term effects of social robot interactions, while systematically addressing assumptions made under the this study's context-specific constraints.

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