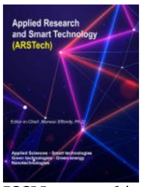
Applied Research and Smart Technology Vol. 3 No. 2 (2022) 81-92

ARS Tech

Applied Research and Smart Technology



Journal homepage: www.journals2.ums.ac.id/index.php/arstech

ISSN 2722-9645

Research Article

Enhancing social responses: Effects of controlling language by a social robot in a decision-making game for human-robot interaction (HRI)

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Permalink (DOI): https://doi.org/10.23917/arstech.v3i2.1187

ARTICLE INFO

Article history:

Received 06 October 2022
Revised 17 November 2022
Accepted 24 November 2022
Available online 27 December 2022
Published regularly 31 December 2022

Keywords:

Decision-making game
Galvanic skin response (GSR)
Human-robot interaction (HRI)
Psychological reactance
Wizard of Oz (WoZ)

ABSTRACT

The rise of technology has induced the development of robots that engage with humans through social interaction. The robot is believed to be capable of assisting humans in their life. However, the current technology is still far from a fully autonomous robot as there are many limitations. Additionally, it is unclear whether the current social robot effectively influences social reactance in Human-Robot Interaction (HRI). The study's objective is to investigate the influence of social cues used by the social robot on human social responses for HRI applications. Also, the study validates the reactance scale used in the questionnaire by correlating the measure with Galvanic Skin Response (GSR) readings. The study proposes a Wizard of Oz (WoZ) approach to observe HRI through decision-making games. A social robot is programmed to persuade participants to make choices. The participants' decisions made during the experiment and their GSR reading are recorded, and then they are asked to answer questionnaires. Statistical analyses are done on the collected data using the regression and MANOVA statistical tests. As a result, there is a significant correlation between GSR reading and enjoyment. Regarding social cues, the participants feel more relaxed when the social robot exhibits social cues in High Controlling Language (HCL) conditions rather than Low Controlling Language (LCL) conditions. Furthermore, the Attitude trait of the social robots greatly influences human perceived social intelligence towards the robot.

1. INTRODUCTION

Social robots have become the most prevalent technology in the market [1] due to the growing interest in using them for therapy [2]. There are eight critical social traits that users characterized as elements in a social robot's ability to look sociable and be accepted [3]. First, 'the capacity of two-way communication' between robots and humans [3]–[5]. Next is the need for robots to dive into the human environment and 'exhibit emotions and 'opinions', 'be socially mindful', 'give social support', and 'behave autonomously' [3], [6]. Furthermore, the robot needs to have a trait of 'cosiness', 'self-identity', and 'mutual respect' [3], [4]. Ultimately, an 'extended framework' for social robotics demonstrates seven important features of social robots [3]. Firstly, the robot should have its 'appearance' [4]. Next, the robot should have the capability to exhibit 'social interaction', 'autonomy', and 'intelligence' [3]. Moreover, the robot's interaction with humans should be in 'proximity', where it communicates using the 'temporal profile of the interaction' and understands the 'context of the interaction' [2], [3], [5], [7].

A robot should be more independent when receiving tasks; therefore, engineers shall design the robots with self-abilities to sense and act accordingly. Although intelligent robots can meet human needs and accommodate the dynamics of the environments independently, they are limited due to their surroundings and most advanced technologies, such as image recognition, sensors, and neural network technology, and brilliant robots are still in development [8]. As such, Human-Robot Interaction (HRI) practitioners and academics have applied scientifically rigorous techniques across the social robot design lifecycle [9]. It is incredibly challenging to consolidate human emotions into measurable metrics [10] and to procure human 'psychological-based' trust rather than 'physics-based' trust [11]. Therefore, studies on human social responses are crucial to identify and validate those social metrics.

Furthermore, quantitative measures are required to support those metrics' validity. A physiological measurement can be carried out when a person is exposed to specific emotional stimuli through physiological indicators like changes in facial expressions, voice, bodily movements, heart rate, and brain activity in conveying their emotions [12]. Then, these signals are utilized to link an individual's emotional state to external stimuli [12]. The physiological signals associated with the autonomic nervous system appear to be an excellent approach to measuring emotional states objectively [13]–[15], such as through Electroencephalography (EEG), skin conductivity, and heart rate [16].

Skin conductance is one of the biological signals that can be used to measure human responses. Galvanic Skin Response (GSR) is a device that constantly measures the voltage reading on human skin, influenced by electrical resistance, as shown in Figure 1. The skin conductance is estimated using Ohm's Law by monitoring the current flow [17]. In an earlier study, the GSR could differentiate stress or relaxation conditions with a success rate of 90.97%. The medium used to elicit the stress condition is a stressful game [18].

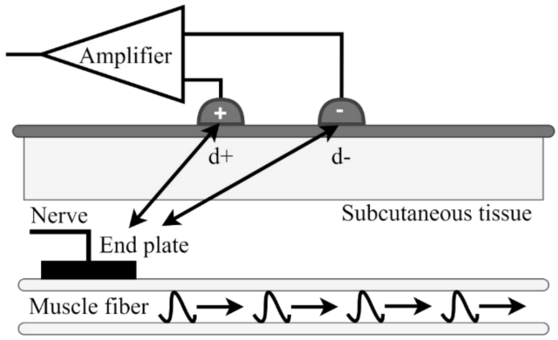

Figure 1. EMG signal transmission in muscle fibres.

In addition, the design of social interaction logic, which defines how the robot behaves and interacts with people, is one of the challenges of introducing robots to new areas [19]. This is because it is time-consuming for an interface designer to build all of a robot's actions by hand, and it isn't easy to anticipate all possible human responses in a social encounter [19]. Hence, this study proposes the Wizard of Oz (WoZ) approach, where a person manages a robot remotely, such as its movement, navigation, voice, gestures, and other functions [9]. WoZ can include any level of autonomy, from totally autonomous to fully teleoperated, as well as mixed-initiative engagement [9]. WoZ is part of an iterative design process to try out early elements of their concept that have yet to be developed entirely [9]. However, WoZ is more of a human-human interaction with a robot as a medium [9].

Additionally, this experimental approach will make it more difficult to develop robots capable of effectively reducing mistakes on their own in the future [9]. Nevertheless, one option to address this methodological concern is to design experiments that use WoZ in a systematic and repeatable fashion, allowing for a more seamless transition to a more autonomous and competent system in the future [9]. Thus, despite the drawback of WoZ, this approach is selected as it helps ease the error handling and the development budget in the experiment.

In the previous project, a few gaps were identified. The persuasive game has a few limitations regarding the social cues of a social avatar which is unlikely to elicit social reactance [20]. Additionally, a small sample size makes the analysis arguable [21]. Lastly, the reliability of the qualitative measures in the earlier studies needs to be validated [22].

Ghazali et al. suggest the WoZ approach as the social robot can interact dynamically with the users. An experimenter is assigned to control the robot from a concealed area close to the experiment location [23]. This approach developed the feedback loop system, which immediately triggers the robot's response of the participant's response. Finally, the participants will be informed of the main goal of the experiment [23].

Furthermore, [20], [23] demonstrate the level of controlling language where the highly controlling language asserts direct opinions while the low controlling language suggests advice respectfully. It is reported that highly controlling language can influence psychological reactance as the robot persuades the users [20], [23]. This reactance then will not comply with the views of the persuadee [23] due to the perceived threat of freedom [24]. This current study monitors psychological reactance and compliance but is validated with physiological responses.

For this study, a social robot, namely Rero, is utilized to mimic human voice expression in addressing the gap of the social cues used in the earlier study [20]. Second, the sample size is extended, and the participants are well-informed about the experiment instructions. Also, the physiological signal is measured to validate the social reactance induced by the participants. Using a developed game as a medium for HRI, the robot is manipulated to convey persuasive messages using either Low Controlling Language (LCL) or High Controlling Language (HCL). Throughout the game, the GSR readings of the participants are measured. At the end of the session, questionnaires are distributed to gauge their social responses toward the interaction. Details of the setups will be explained in the following sections.

2. MATERIALS AND METHOD

In this section, the development of the persuasive game is elaborated using a few strategies: the 'transfer effects', 'effects type', 'change type', and 'point of impact' [25]. Then, the details of experimental setups are described; besides the measures used in the questionnaires, the score of GSR reading and compliance are elaborated.

2.1. Game development

Siriaraya et al. [25] first suggest defining the 'transfer effects' in designing a persuasive game. 'Transfer effects' is the deliverable objectives of experiencing the game world. There are a few 'transfer effects', namely 'effects type', 'change type', and 'point of impact'.

'Effects type' results from playing persuasive games [25]. In this experiment, the game is designed to enhance the perceptual effects of the players, mainly on how to survive on a stranded island. Specifically, the participants will be asked to make several selections in finding food, water, and shelter.

Upon persuasion, the 'change type' needs to be selected to form new behaviours, whether reinforcing, altering, or encouraging the player [25] to change his or her mind. In this experiment, a robot named Sara persuades the players to alter all their choices. The game flow is modelled to persuade the player to change their mind, regardless of his or her choices. For example, in determining which food the player would choose to eat to survive, if player A prefers another food rather than 'Tuna' as his or her initial food choice, Sara will persuade them to choose 'Tuna'.

Additionally, Siriaraya et al. also mention that game designers need to set when the 'point of impact' or expected time frame would the games to influence the players to form the new behaviours, whether for a short time or a longer time [25]. Therefore, this project has created a few phases for when and how the 'points of impact' occur. As demonstrated in Figure 2, the point of impact is set to happen at an instance when Sara persuades the player. Consequently, the player must change their decision, similar to Sara's. Therefore, every time Sara convinces the player, the time will be recorded, as it is believed that the player's social reactance signal is differed before and after the 'point of impact'.

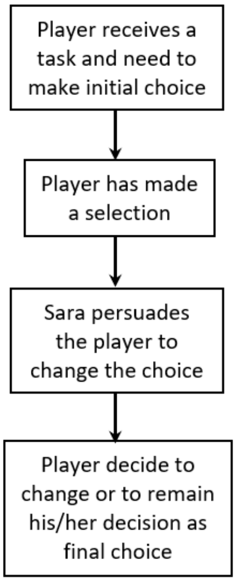

Figure 2. The flow of a task. 'Point of Impact' at the moment of persuasion.

2.2. Game design

Sara is portrayed as a teenage girl with a slow-paced and strong voice. The scenes in the game are also designed to be an exploration trip where the scenes take place on a stranded island. The tasks are clear and straightforward; moreover, each scene has its correlation, which helps the players to understand the tasks better. Sara is programmed to execute dialogues that contain two levels of controlling language: low and high controlling language. The controlling language is expected to influence the players' social reactance; thus, effective controlling dialogues must be prepared to succeed in the 'transfer effects' as suggested by [25]. Sara would persuade the player leniently using wording like "Would you" to demonstrate low controlling language.

On the other hand, in the highly controlling language condition, Sara would use strict words such as "You must" [20]. Positively managing language aims to achieve a greater possibility of compliance [23]. However, the reactance response [20] might be high due to the coercive language used during a robot persuasive attempt.

2.3. Informed consent

The participants must sign a consent form just before beginning the experiment. The form contains the aim and benefit of the study, the procedures and the risks. It also mentions the expected duration of the investigation and targeted participants. Finally, it also emphasizes the voluntary confidentiality of the participants' information.

2.4. Participants

A sample of forty undergraduate students is recruited among the IIUM students between 20 and 24 years old. The experiment took thirty minutes; each volunteer was given a snack as a token of appreciation. There is no restriction on age, gender, and nationality.

2.5. GSR device

A GSR sensor is connected to a breadboard and an Arduino Uno microcontroller, as shown in Figure 3. The breadboard is used to configure a switch, while the Arduino Uno is programmed to collect the GSR data. The collected data is then saved in Excel using Tera Term software. The GSR finger glove is put on the non-prominent hand as the other hand will be used to play the game. The GSR data will be recorded from the beginning of the game until the end. At the end of the experiment, the participants will switch the GSR device off.

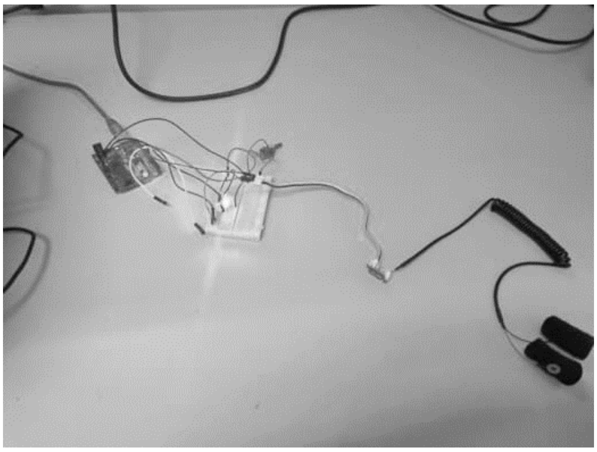

Figure 3. GSR device setup.

2.6. Rero robot

This project uses the Rero robot (see Figure 4) to give instructions and advise players to change their minds in making decisions.

Figure 4. Sara, the game instructor robot.

The robot is placed in front of the participants and connected to the wizard's computer via a micro-USB cable, as shown in Figure 5.

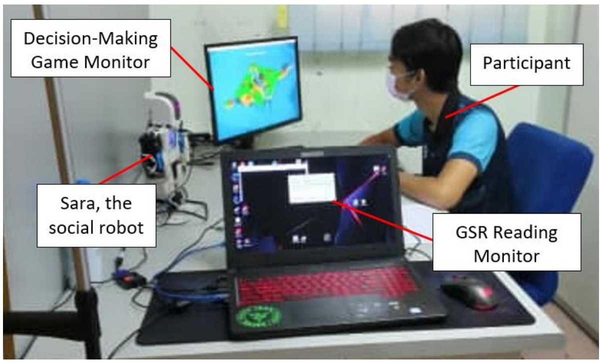

Figure 5. Experimental setups.

2.7. Experimental setups

The participants will play the designed persuasive games individually in an isolated space. They need to listen carefully to the instructions given by Sara, the game instructor robot. Ten tasks must be completed, and they are free to decide their own choices for each task. Then, Sara, a wizard who controls that, exhibits social cues to persuade them to choose her choice.

To demonstrate, in the first task, Sara asked the participants to decide which food they would like to eat. As the participants have picked food that is not 'Tuna' as their choice, Sara instantly refuses to accept the selection and suggests choosing 'Tuna', and then the game proceeds to the second attempt. Otherwise, if they pick 'Tuna' (Sara's choice) on the first attempt, Sara would agree with them; this is also applied to the second attempt of the task. This process is then cycled for every job, ten lessons.

Each task has at most two attempts where the game will promptly proceed to the next task if the participant chooses Sara's choice on the first attempt. As the 'point of impact' is at the moment of Sara's persuasion, therefore, the time of 'before' (the beginning of the task), 'instant', and 'after' (the end of the task) is recorded to be analyzed with the GSR data.

At the end of the game, all participants' choices and recorded timestamps are saved in a JSON file.

2.8. Wizard of Oz (WoZ)

The experimenter will monitor the participants' choices and control Sara's audio by uploading them (clicking the 'Start' icon) using Rero Planner software. As there will be too many possibilities, the multiple Rero Planner applications are opened, and all RRP files (Rero Planner files) are created before the experiment, as shown in Figure 6.

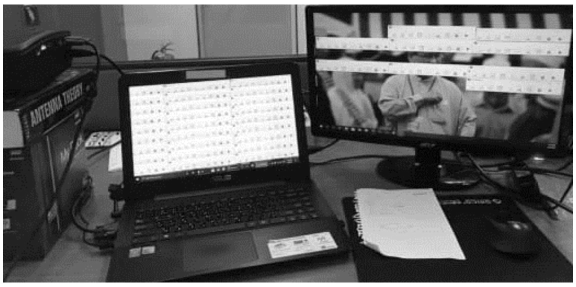

Figure 6. Wizard perspective and control.

2.9. Experiment process

The study design is summarized in Figure 7. In Phase 1, participants are given a consent form and put on the GSR device. Then, in Phase 2, the participants will listen to 3-minute music to relax and record their GSR value. The participants are randomly assigned to 2 conditions (language coerciveness: high vs low) of controlling language in a within-subjects experimental design. Twenty participants are involved in each situation. Subsequently, they will play the decision-making game with the advice of Sara at the next phase, and they will proceed to the next task after the second attempt or Sara's choice is selected. The task will end at the tenth task, and all the gameplay data will be saved. Lastly, they must switch off the GSR device and continue to answer the questionnaires.

2.10. Measurements

As suggested in [23], questionnaires were redesigned but retained the essence of the questions—refer to Table 1. These questionnaires were constructed in [23] 's previous technology acceptance study. The metrics of Usefulness, Ease of Use, Attitude, Intention, Enjoyment, Reactance, Liking, and Belief are assessed using a 5-point Likert scale, ranging from disagree (1) to agree (5) totally. In contrast, the Compliance score is a binary score in each task where each task that the participants follow the robot's advice would score 1, otherwise 0.

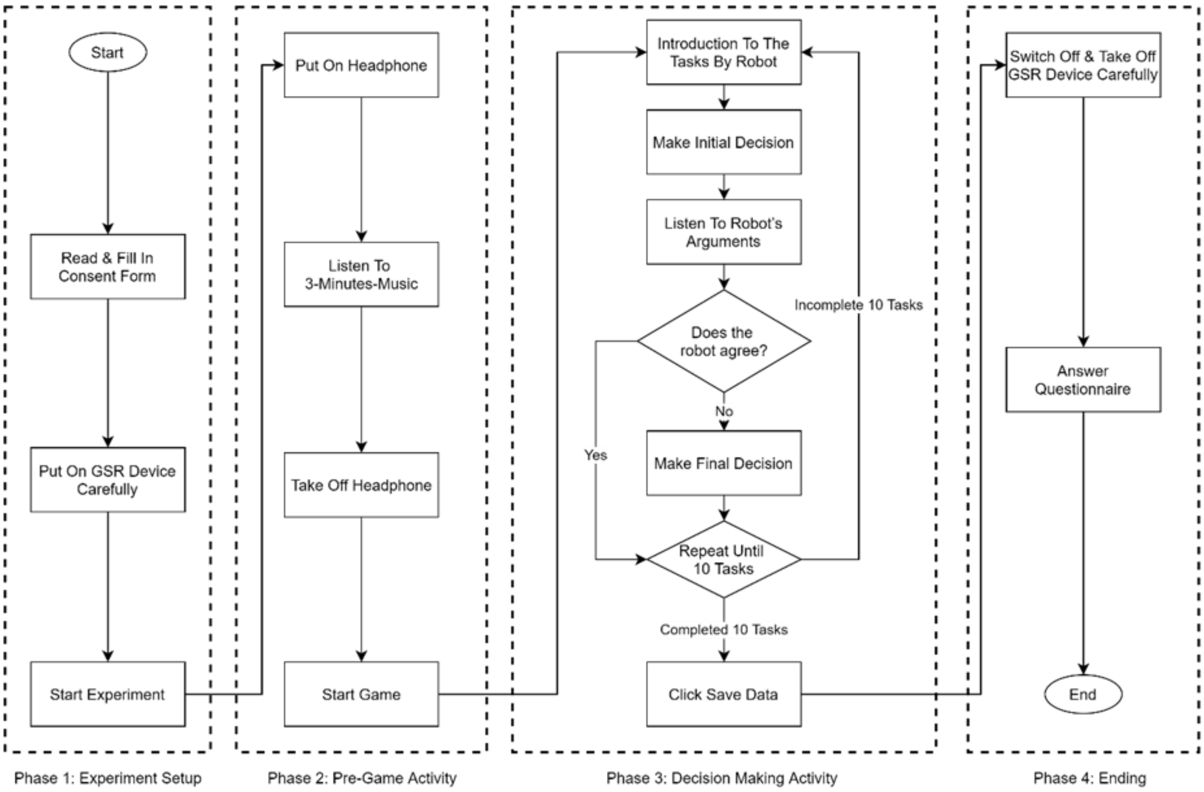

Figure 7. The experimental flowchart.

The GSR data is converted into a discrete number of -1, 0, and 1 where annotation of decreasing GSR reading, null reading, and increasing GSR reading, respectively. The annotation is made as GSR readings at two phases of each task (before and after persuasion) are averaged and compared, thus having a single discrete value at the specific task. The null reading is present as there is a task in which the participants choose Sara's choice on the first attempt. Therefore, the second attempt is skipped to the next task. The separating by each timestamp and averaging of the data is made using Matlab software.

Using SPSS software, some statistical tests will be done to analyze the effect of social cues on the participants' reactance. Using the regression and Multivariate Analysis of Variance (MANOVA) statistical test, the F-value is gained while the α-value is set to 0.1. Additionally, the mean and standard deviation are also obtained for further analysis.

Table 1. Metrics used to evaluate the tested model.

Usefulness
I can decide more quickly and easily which choice to choose without using Sara's advice.
I can better decide which choice I want to choose without using Sara's advice.
I am better informed about the suggested choice.
I can decide more quickly and more easily whether I want to use the choice suggested by Sara or not.
I can better decide whether I want to use the choice suggested by Sara or not.
Ease
Interaction with Sara is clear and understandable.
Interaction with Sara does not need to require a lot of mental effort.
I find it easy to follow Sara's advice.
I believe that the use of Sara is trouble-free.
Attitude
I have a favorable attitude toward Sara.
I like the idea of Sara providing information about choice in every task.
I believe that Sara is beneficial in the decision-making situation.
Using Sara to improve my knowledge about the choices would be a good idea.
Intention
Assuming I have access to Sara again, I would intend to use it.
Assuming I have access to Sara again, I predict that I would use it.
Assuming I have access to Sara again, I would certainly use it.
Assuming I have access to Sara again, I would say something favourable about Sara.
Enjoyment
I would find using Sara to be enjoyable.
I would find using Sara to be fun.
I would find using Sara to be entertaining.
I would find using Sara to be exciting.
Reactance
I feel irritated towards Sara.
I feel angry with Sara.
I feel annoyed towards Sara.
I feel aggravated towards Sara.
Liking
Sara was approachable.
Sara was confident.
Sara was likable.
Sara was trustworthy.
Sara was interesting.
Sara was friendly.
Sara was sincere.
Sara was warm.
Sara was competent.
Sara was informed.
Sara was credible.
Sara was modest.
Sara was honest.
Belief
Sara behaves in an ethical manner.
I am confident of the intentions, actions, and outputs of Sara.
I am not wary of Sara.
I am confident with Sara.
I will trust Sara if she gives me advice again in the future.
I trust that Sara can provide me with the best advice.
I will follow the advice that Sara gives me.
Compliance
The compliance score is measured by the total of advice in each task complied by the participants during robot persuasion.

2.11. Hypothesis

There are three independent variables (IV) collected, which are Controlling Language (CL) (IV1), Gender (IV2), and Age (IV3).

There are ten dependent variables (DV) collected, which are GSR (DV1), Compliance (DV2), Usefulness (DV3), Ease (DV4), Attitude (DV5), Intention (DV6), Enjoy (DV7), Reactance (DV8), Liking (DV9) and Belief (DV10).

Hypothesis 1: Correlation among dependent variables. T

There is a significant correlation among DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10 when using the robot.

Hypothesis 2: Main effect of IV on DV.

There is a significant main effect of IV1 on DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10.

Hypothesis 3: Interaction effect of IVs on DV.

Hypothesis 3(a), There is a significant interaction effect of IV1 & IV2 on DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10.
Hypothesis 3(b), There is a significant interaction effect of IV1 & IV3 on DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10.

Hypothesis 4: Simple main effect and interaction effect of IVs on each GSR (DV1) and Compliance (DV2) phase.

Hypothesis 4(a), There is a significant simple main effect of IV1 on each GSR phase.
Hypothesis 4(b), There is a significant interaction effect of IV on each GSR phase.
Hypothesis 4(c), There is a significant simple main effect of IV1 on each Compliance phase.
Hypothesis 4(d), There is a significant interaction effect of IV on each Compliance phase.

3. RESULTS AND DISCUSSION

3.1. Hypothesis testing

Hypothesis 1: Correlation among dependent variables

There is a robust, positive correlation between DV5 and DV6 (r(38) = .87, p < .10). This has been suggested by [26] that if there is no privacy violation and the robot is ethically programmed (DV5), the participants intend to conform the robot (DV6). In addition, there is a strong, positive correlation between DV7 and DV9 (r(38) = .70, p < .10). This is logical as both share almost the same attributes. Besides that, there are strong, positive correlation between DV6 and DV4 (r(38) = .70, p < .10), DV6 and DV9 (r(38) = .75, p < .10), DV6 and DV10 (r(38) = .75, p < .10), and DV9 and DV10 (r(38) = .72, p < .10). As DV9 and DV10 relate to each other, it is not surprising both would correlate with DV6. Additionally, [26]–[28] demonstrate that the participants intend (DV6) to follow the robot's suggestion due to trust (DV10) and their fear of taking a risk (DV4). Furthermore, there are strong, positive correlation between DV5 and DV7 (r(38) = .63, p < .10), DV5 and DV9 (r(38) = .70, p < .10), and DV5 and DV10 (r(38) = .62, p < .10). These results has proven [29] 's suggestion where 'Preference touch sensation' (DV5) develops their enjoyment (DV7) and liking (DV9) as the participants' first impressions. In addition, [26], [30] propose that if the interrogation of the robot does not behave unexpectedly and violates participants' privacy, this ethics (DV5) will lead to belief emergence (DV10). On the other hand, there are robust and negative correlations between DV8 and DV10 (r(38) = -.61, p < .10), which concludes that if the participant feels threatened, their belief (DV10) will lower [26].

Table 2. Correlation table among DVs (r: Pearson Correlation, p: Sig. (1-tailed)).

		GSR	Compliance	Usefulness	Ease	Attitude	Intention	Enjoy	Reactance	Liking	Belief
GSR	r	1.00	0.04	0.17	0.02	0.13	-0.02	0.25	0.12	-0.02	-0.14
	p		0.40	0.14	0.44	0.21	0.46	0.06	0.23	0.46	0.19
Compliance	r	0.04	1.00	-0.30	0.15	0.01	0.02	-0.14	0.17	-0.11	0.02
	p	0.40		0.03	0.17	0.48	0.45	0.20	0.14	0.24	0.46
Usefulness	r	0.17	-0.30	1.00	0.19	0.38	0.31	0.31	-0.15	0.15	0.05
	p	0.14	0.03		0.12	0.01	0.02	0.02	0.17	0.18	0.37
Ease	r	0.02	0.15	0.19	1.00	0.54	0.70	0.52	-0.41	0.60	0.60
	p	0.44	0.17	0.12		0.00	0.00	0.00	0.00	0.00	0.00
Attitude	r	0.13	0.01	0.38	0.54	1.00	0.87	0.63	-0.53	0.70	0.62
	p	0.21	0.48	0.01	0.00		0.00	0.00	0.00	0.00	0.00
Intention	r	-0.02	0.02	0.31	0.70	0.87	1.00	0.58	-0.60	0.75	0.75
	p	0.46	0.45	0.02	0.00	0.00		0.00	0.00	0.00	0.00
Enjoy	r	0.25	-0.14	0.31	0.52	0.63	0.58	1.00	-0.55	0.70	0.51
	p	0.06	0.20	0.02	0.00	0.00	0.00		0.00	0.00	0.00
Reactance	r	0.12	0.17	-0.15	-0.41	-0.53	-0.60	-0.55	1.00	-0.57	-0.61
	p	0.23	0.14	0.17	0.00	0.00	0.00	0.00		0.00	0.00
Liking	r	-0.02	-0.11	0.15	0.60	0.70	0.75	0.70	-0.57	1.00	0.72
	p	0.46	0.24	0.18	0.00	0.00	0.00	0.00	0.00		0.00
Belief	r	-0.14	0.02	0.05	0.60	0.62	0.75	0.51	-0.61	0.72	1.00
	p	0.19	0.46	0.37	0.00	0.00	0.00	0.00	0.00	0.00	

Moreover, there are moderate, positive correlation between DV4 and DV5 ($r(38) = .54$, $p < .10$), DV4 and DV7 ($r(38) = .52$, $p < .10$), DV4 and DV9 ($r(38) = .60$, $p < .10$), DV4 and DV10 ($r(38) = .60$, $p < .10$). Similarly, [26] report that good ethics (DV5) will improve trust (DV10) and ease of use (DV4). On top of that, there are moderate, positive correlation between DV7 and DV6 ($r(38) = .57$, $p < .10$), DV7 and DV10 ($r(38) = .51$, $p < .10$). However, there are moderate, negative correlation between DV8 and DV4 ($r(38) = -.41$, $p < .10$), DV8 and DV5 ($r(38) = -.53$, $p < .10$), DV8 and DV6 ($r(38) = -.60$, $p < .10$), DV8 and DV7 ($r(38) = -.55$, $p < .10$), DV8 and DV9 ($r(38) = -.57$, $p < .10$). As an inference, the participants would feel irritated (DV8). They thus would not intend to use (DV6), despise (DV7) and dislike (DV9) the robot if it exhibits a bad attitude (DV5) and burdens them (DV4).

Moreover, there are weak, positive correlation between DV1 and DV7 ($r(38) = .25$, $p = .06$). Therefore, this proves that the GSR reading (DV1) connects with the participants' enjoyment (DV7). Next, there are weak, positive correlation between DV3 and DV5 ($r(38) = .38$, $p = .01$), DV3 and DV6 ($r(38) = .31$, $p = .02$), DV3 and DV7 ($r(38) = .31$, $p = .02$). To prevent from risk. The participants find that the robot's usefulness (DV3) is a great attitude (DV5) which also triggers their enjoyment (DV7) and intention to use them (DV6). On the other hand, there is a weak, negative correlation between DV2 and DV3 ($r(38) = -.30$, $p = .03$), DV2 and DV8 ($r(38) = .17$, $p = .14$). As the participants feel pressured (DV8), it is reported that they would not comply with the robot advises (DV2) [26].

Apart from that, there is a very weak, positive correlation between DV1 and DV3 ($r(38) = .17$, $p = .14$). As the robot is helpful (DV3), the participants feel less stressed a bit (DV1) because it assists them in eliminating their indecision during the game. Lastly, there is a very weak, positive correlation between DV3 and DV4 ($r(38) = .19$, $p = .12$). This can be concluded that even though the robot is easy to use (DV4), it is slightly helpful (DV3) as the participants need reasonable advice to understand the game.

Hypothesis 2: Main effect of IV1 on DV

There was a significant main effect of IV1, *Wilks' Lambda* = 0.62, $F(39) = 1.79$, $p = 0.11$. In addition, there is a significant main effect of IV1 on DV1, $F(39) = 3.61$, $p = 0.07$. This validates that CL (IV1) influences the participants' social reactance (DV1). Additionally, there is a significant effect of IV1 on DV4, $F(39) = 3.96$, $p = 0.05$. To infer, the participants might feel puzzled by the robot's behaviour and resulting in feeling uneasy using them. Moreover, there is a significant effect of IV1 on DV9, $F(39) = 2.27$, $p = 0.14$. It is suggested that CL could enhance the participants' enjoyment [31]. Additionally, the GSR sensor measured a higher skin response when Sara, the robot, used HCL ($M = 2.95$, $SD = 2.33$) rather than LCL ($M = 0.80$, $SD = 3.61$); this also can be concluded that participants felt more relax in HCL condition than LCL condition, this may be that the participants feel less ambiguous with straightforward advice from the robot. However, participants feel more at ease using Sara, the robot, in the LCL condition ($M = 4.45$, $SD = 0.58$) than in the HCL condition ($M = 4.01$, $SD = 0.80$). They might feel puzzled during HCL conditions and thus feel unease using them. Furthermore, participants like Sara, the robot, more when she used LCL ($M = 4.42$, $SD = 0.53$) than HCL ($M = 4.17$, $SD = 0.54$). [32] indicate that the participants feel displeased by the robot if it is oppressive.

Table 3. Tests of between-subjects effects of CL(IV1) on DVs.

Source		Mean Square	F	Sig.
CL	GSR	52.90	3.61	0.07
	Compliance	0.40	0.04	0.85
	Usefulness	0.17	0.32	0.57
	Ease	1.91	3.96	0.05
	Attitude	0.04	0.11	0.74
	Intention	0.51	0.82	0.37
	Enjoy	0.10	0.11	0.75
	Reactance	0.10	0.11	0.74
	Liking	0.64	2.27	0.14
	Belief	0.20	0.45	0.51

Hypothesis 3: Interaction effect of IVs on DV

Hypothesis 3(a):

There is no significant interaction effect of IV1 & IV2 on DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10, *Wilks' Lambda* = 0.85, $F(39) = 0.46$, $p = 0.90$.

Hypothesis 3(b):

There is no significant interaction effect of IV1 & IV3 on DV1, DV2, DV3, DV4, DV5, DV6, DV7, DV8, DV9, and DV10, *Wilks' Lambda* = 0.18, $F(39) = 1.16$, $p = 0.28$.

Hypothesis 4: Simple main effect and interaction effect of IVs on each GSR (DV1) and Compliance (DV2) phases

There is a significant change of GSR (DV1) in each task, *Wilks' Lambda* = 0.37, $F(39) = 3.27$, $p < 0.02$. Based on the analysis in Figure 8, the participants felt stress at the beginning of the tasks, then gradually relaxed until the end of the functions. This trend also can be seen in [27], [28], where the participants could figure out that the robot is trying to build their norm.

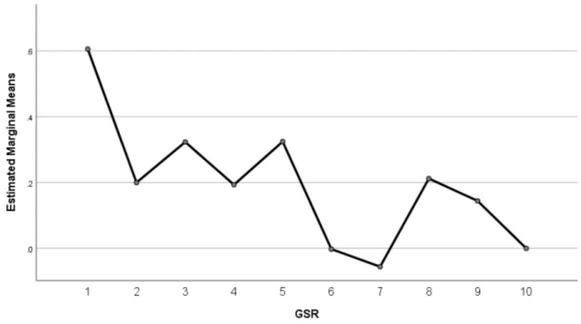

Figure 8. Estimated marginal means plot of each GSR (DV1) phase.

Hypothesis 4(a): There is no significant simple main effect of IV1 on GSR (DV1) on each task, *Wilks' Lambda* = 0.55, $F(39) = 1.54$, $p = 0.21$.

Hypothesis 4(b): There is no significant interaction effect of IV1 on GSR (DV1) on each task.

Hypothesis 4(c): There is a significant simple main effect of IV1 on Compliance (DV2) on each task, *Wilks' Lambda* = 0.47, $F(39) = 1.80$, $p = 0.14$. Additionally, there is a significant simple main effect of IV1 on Compliance 3 (at the third task of the experiment), $F(39) = 3.97$, $p = 0.06$, and on Compliance 5 (at the fifth task of the experiment), $F(39) = 2.35$, $p = 0.14$. In a third task, participants tended to follow the robot that used HCL ($M = 0.64$) more than LCL ($M = 0.10$). On the other hand, participants tend to follow the robot in the LCL condition ($M = 0.42$) than in the HCL condition ($M = 0.23$) at the fifth task. In conclusion, the participants defied the robot's suggestion in the HCL condition in the fifth task due to their awareness of the game flow while conformed to it in the HCL condition in the third task as they still contemplated the game flow.

For hypothesis 4(a), there is a significant interaction effect of IV1 and IV3 on Compliance (DV2) on each task, *Wilks' Lambda* = 0.07, $F(39) = 1.60$, $p = 0.05$. In addition, there is a significant interaction effect of IV1 and IV3 on Compliance 10 (at the tenth task of the experiment), $F(39) = 2.85$, $p = 0.05$. In the tenth task, the participants who are 20 years old would highly follow the robot's suggestions in the HCL condition ($M = 1.00$). However, the participants who were 24 years old would follow the robot's advice in the LCL condition ($M = 0.50$) but would refuse to follow the robot's suggestion in the HCL condition ($M = -0.50$). Furthermore, those 21 ($M = 0.50$) and 23 ($M = 0.25$) years old tend to agree with the robot's recommendation in LCL condition at the tenth task. In addition, 22-year-old participants tend to follow the robot's advice in LCL ($M = 0.33$) and HCL ($M = 0.40$) conditions in the tenth task. Thus, this indicates that the younger participants tend to obey the robot's persuasion (HCL condition) as they might be indecisive; conversely, they most likely accept the suggestion in the LCL condition.

The study finds the tested model to be effective. It is reported that if the social robot is programmed ethically, thus no privacy is violated, the users would believe and intend to use it. Furthermore, the result suggests that if the social robot can interact socially, this would develop their enjoyment and liking. On the other hand, if the users feel threatened, it will lower their belief. Besides that, a significant finding validates that the GSR signal correlates with their enjoyment. In addition, their GSR signal was recorded to be lower or less stressful as the social robot is helpful. Moreover, the result discovers that CL does influence social reactance.

Additionally, the CL does control the ease of use of the robot, as the users might feel puzzled by the robot's behaviour. Moreover, the CL could enhance their enjoyment. Nevertheless, it is revealed that the users feel more relaxed in the HCL condition. This may be because they feel less ambiguous with the robot's persuasion. Nonetheless, the users would feel unpleasant if the social robot is oppressive.

On top of that, the result suggested that the participants' stress was lower throughout the experiment. This might be because they had figured out the flow of the investigation. This trend can be further observed in the HCL condition, and the participants comply with the social robot's suggestion less in the third task than in the fifth task. As they contemplate the game flow in the third task, they are aware of it in the fifth task. Finally, it is reported that the younger participants tend to comply with the robot's persuasion in the HCL condition as they might feel puzzled by the game flow. However, most participants abide by the LCL condition due to the robot's leniency.

4. CONCLUSION

The experiment has been accomplished to investigate the influence of social cues on human social reactance by the social robot. HCL condition is proven to make the participants feel more relaxed than the LCL conditions. In addition, the experiment validates that the controlling language has influenced the GSR device. Thus, their social reactance is elicited. Moreover, an ethical, social robot improves the participants' enjoyment, liking, and belief.

Additionally, they intend to use the social robot; when it has a good attitude, is easy to use, and is trustworthy. However, their belief score would lower if they felt irritated with the social robot's attitude and inconvenience. Next, they would not intend to use, disobey, despise or dislike the social robot.

Furthermore, the findings show that usefulness is connected to the social robot's attitude, and it reduces the participants' stress a bit. Nevertheless, it poorly indicates that the social robot is easy to use. Besides that, the participants tend to follow the social robot's suggestions in HCL conditions. Still, the social robot tends to be likeable and makes the participants feel at ease using it in LCL conditions. Thus, these findings suggest the importance of social cues in HRI. This is to improve the social interaction between them in various fields. Furthermore, using the physiological signal to measure the social reactance would help the social robots actively monitor their performance in social interaction. Lastly, the WoZ approach assists the study of HRI in understanding the characteristics of the social robot to guide the future design of social robots.

To improve the previous limitations and errors, the number of participants should be increased to enhance the reliability of the result. The game design needs to be revised so the participants understand the interface. Aside from that, another physiological device, such as measuring the EMG device, could be used to compare with the GSR device. Besides, the future experiment will include another social cue which is the gender of the social agents, as it is reported that opposite persuasive social agents are more trustworthy and engaging rather than the similar gender.

CONFLICTS OF INTEREST

To the best of the author's knowledge, this publication is not influenced by any competing interests.

ACKNOWLEDGEMENT

The authors would like to thank the International Islamic University Malaysia for assisting with this study.

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