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RESEARCH ARTICLE

Enhancing Decision-Making Based on Social Responses for Human-Robot Interactions (HRI) Applications

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ABSTRACT - Making decisions, especially in uncertain situations, can be challenging. This study explores how a social robot, acting as an advisor, affects human decision-making in a specially designed game. The social robot facilitated the decision-making process using verbal cues in a study with a 2x2 between-subject (controlling language and social praise) design experiment. Drawing from the Technology Acceptance Model (TAM) and the Persuasive Robots Acceptance Model (PRAM), the study assess how human responses influence the acceptance of this technology. Sixty participants took part in the experiment, and as results, their anxiety levels decreased after interacting with the robot and playing the game. Also, the outcomes highlight positive social responses, suggesting that social robots have potential in supporting decision-making even though the specific impact of social cues on participant responses is somewhat limited. Also, significantly, the coefficient of determination, R2 for Intentions as modelled by TAM, experienced a 0.236 increase with the incorporation of social responses in the acceptance modelling via PRAM. In conclusion, incorporating social responses such as liking and beliefs enhances the ability to predict acceptance, emphasizing the importance of considering social aspects in the acceptance of robots. This research contributes to the understanding of Human-Robot Interactions (HRI) and provides valuable insights for future developments in social robots for decision-making support.

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1.0 INTRODUCTION

A person's daily actions are intricately woven with choices, ranging from inconsequential to potentially impactful outcomes. From the moment we wake up, we face a series of choices. The first decision is right in the morning—do we take a refreshing bath or sip clear, invigorating water? As the day turns to night, another decision comes our way. The setting is different now, with shadows all around, and we need to think about how we want to be comfortable during the night. Should we stick with the quiet breeze from the fan or bring in the cool comfort of the air conditioner for a modern touch?

Navigating unfamiliar situations without guidance poses a formidable challenge, making decision-making demanding. The absence of clear direction in such scenarios can significantly contribute to heightened stress levels. Stress and anxiety, particularly those involving risk and potential regret, contribute to the complexity of the decision-making landscape [1]. On one side, regret and disappointment, nuanced emotions, stem from different sources, adding intricacy to the emotional aftermath of decisions [2]. On the flip side, when someone makes the right decision, it brings joy and excitement. This positive experience may motivate them to make more choices with enthusiasm. The various ways individuals react and interact with these robotic entities in a social context is known as social responses. These responses encompass a range of emotions, attitudes, and behaviors that humans exhibit when engaging with others, including social robots [3].

Earlier studies highlighted the importance of social responses in the acceptance of using some technologies in the future. The technologies include mobile apps [4], e-commerce [5] and social robots [6]. Technology Acceptance Model (or known as TAM) has been used widely to predicts people’s intention to use technology based on several key determinants like attitude toward using and intentions to use the technology again in the future [7]. TAM is crucial in developing technologies because it provides information on the potential success of a technology in the market besides enhancing likelihood of creating technologies that align with users' needs and preferences. This structured framework not only can identify key factors influencing users' acceptance, it also can consider other factors beyond mere functionality, by focusing on aspects that contribute to a positive user response [8, 9]. In line with that, a modified TAM known as Persuasive Robots Acceptance Model (PRAM) have been developed by incorporating social responses such as liking and trust towards social robots as key determinants of acceptance toward this technology. This modification enhances the model's predictive power, offering a more nuanced and comprehensive understanding of users' attitudes in the context of HRI using structural equation modelling (SEM) technique [10]. From PRAM, it can be concluded that users' acceptance is not solely based on functionality of a technology, but also on the quality of the social interaction [11].

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The emerging field of social robots holds promise as a helpful support for decision-making. Like how making the right and wrong choices brings happiness and reactance, social robots can assist by offering guidance in the decision-making experience [12, 13]. Interestingly, in the development of social robots, it is essential to incorporate social cues as they serve as the language through which these robots communicate with humans, ensuring a more natural and effective interaction [14]. Social cues are signals, both spoken and unspoken, that a robot uses in Human-Robot Interaction (HRI) to share information and interact with people socially. These cues imitate the communication signals humans use in social situations, such as facial expressions, gestures, body language, and tone of voice. When robots incorporate social cues, the interactions feel more natural and relatable than the robots without social cues [15].

To explore human responses to social cues exhibited by robots, researchers propose the development of decision-making games. Ghazali et al. (2020) advocate for creating a controlled, immersive environment that mirrors real-life challenges in making donations to selective NGOs [11], while Smiderle et al. (2020) connect positive behavioral changes to gamified educational tools [16]. Flogie et al. (2020) highlight the necessity for customizability in decision-making games, catering to diverse participant needs or objectives of the study [17].

Investigating the impact of robots on decision-making, this research introduces two verbal cues—controlling language (high vs. low) and social praise (presence vs. absence). While much research has explored the supportive capabilities of social robots, this study directs attention toward understanding how social cues affect interactions between humans and robots. The study identifies shortcomings in existing TAM [7] when applied to social robots, underscoring the distinctive aspects of HRI by integrating social responses into the acceptance model, same to the approach in PRAM [11]. Leveraging games as a platform for decision-making, a social robot equipped with specific social cues endeavors to influence individuals in their decision-making processes. The design of both the game and the robot prioritizes avoiding the elicitation of anxiety among users during the decision-making activities. In sum, this study mainly aims to test the following hypotheses:

a) Hypothesis 1: Participants are expected to demonstrate low anxiety levels after engaging in the decision-making game.
b) Hypothesis 2: Positive social responses are anticipated from participants after their interaction with the social robot (with dedicated social cues).
c) Hypothesis 3: Positive influence of social responses on the predictive power of PRAM (compared to TAM).

2.0 METHODS AND MATERIAL

The execution of this study adhered to ethical standards and received approval from the IIUM Research Ethics Committee (IREC 2022-044). All participants provided written informed consent, detailing the study's purpose, procedures, duration, and potential risks or discomforts associated with their participation.

2.1 Participants

A total of 60 individuals (41 males and 19 females) participated in the experiment, with ages ranging from 19 to 25 years (M = 22.17, SD = 1.29). The experimental sessions lasted approximately 60 minutes, and participants received MYR 15 in cash as a gesture of appreciation. Selection of participants was based on registrations from responses to advertisements posted outside the laboratory, with no race and nationality restrictions in place.

2.2 Decision-Making Game

The study focuses on using the Ren'Py game engine to develop serious games, particularly those simulating decision-making scenarios for ambiguous selections. Themed as an "Escape Room," the game consists of eight rooms, each offering challenges with diverse solutions for escaping a confined building. The various states of the game can be illustrated through a series of individual "rooms," each presenting its own set of challenges or problems. Figure 1 shows an example of the challenges faced by participants in Room 1.

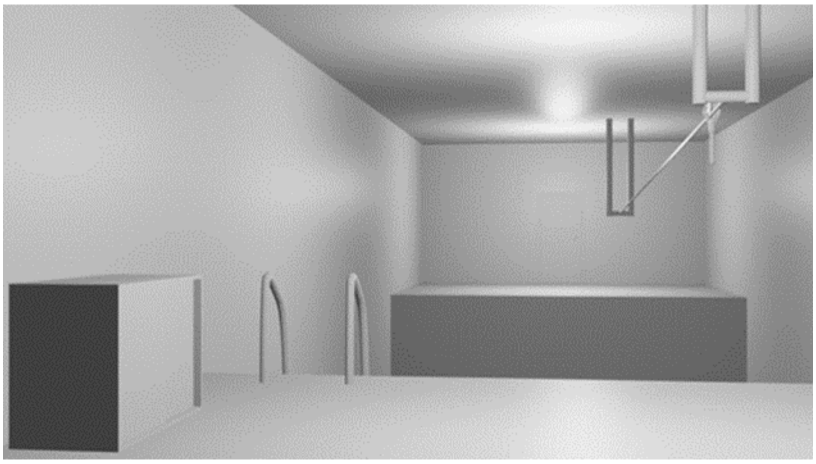

Figure 1. Crossing a zipline

Participants were required to use the zipline for progression but encountered an issue with insufficient grip on the zipline handle. To overcome this obstacle, they were presented with various glove options, as depicted in Figure 2.

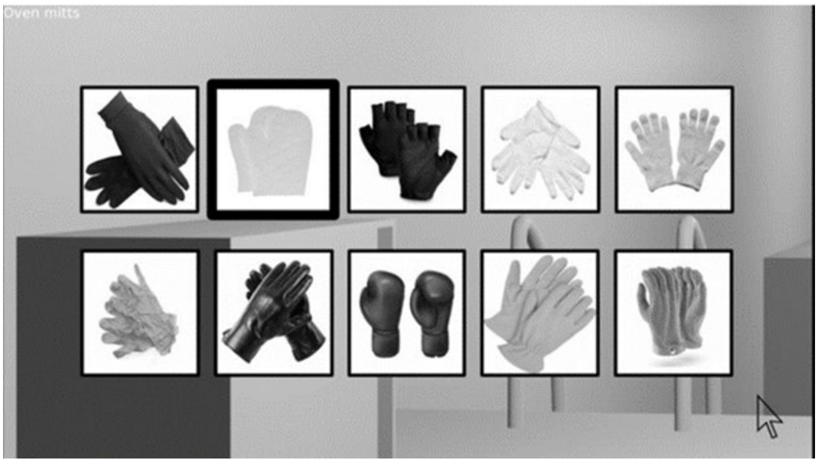

Figure 2. Choice 1: Selection of gloves to cross the zipline

Following the identification of a problem, prompts for choices will be presented twice: initially after the problem is identified, and again after the participant makes their initial choice. In certain rooms, text is utilized instead of images, as the context provided to the participant for resolving the challenge may differ. Similar to most rendered assets, the options provided are monochromatic to avoid bias. The content of prompts will vary depending on the room in which the prompt was triggered. At each choice prompt, the three main user interface elements presented are the options themselves, a text caption at the top left of the screen that appears when the participant hovers the cursor over an option, and a cursor icon at the bottom right, denoting the use of the mouse for game interaction. Challenges range from crossing a ditch to hitting targets, emphasizing problem-solving and physical capability.

2.3 Procedure

Participants were randomly assigned to four groups, each representing a different social cues modality, and engaged with a robot in a two-by-two experimental design (high vs. low controlling language and with vs. without social praise). The experiment began with participants being guided to a separate room for the introduction and consent form process. Before the experiment started, participants read and signed the consent form, followed by filling out a baseline questionnaire on anxiety perception.

Afterward, participants, seated comfortably, completed the first questionnaire through a Google Form on a monitor screen. The experimenter then introduced a button-activated buzzer for privacy and demonstrated its use. After completing the first questionnaire, participants used the buzzer to call the experimenter back. The experimenter returned to demonstrate the game, using a demo version to explain basic elements and interaction methods.

Following the demonstration, participants could ask questions, and the experimenter prepared for the full game. Before launching it, the experimenter explained the game's automatic exit and the appearance of the second questionnaire. The second questionnaire collected data on anxiety perception and the perception of aspects exhibited by the robot.

After the experimenter left, participants started the game by clicking on the door. The social robot, namely Alphamini robot (depicted in Figure 3) introduced itself and provided context for the game setting. Since the inception of the experiment, the robot has consistently emphasized to the participants that there are no right or wrong answers in the game. Consequently, participants hold equal social power with the robot in decision-making. Moreover, suggestions put forth by the robot are entirely random, thereby ensuring the absence of any bias.

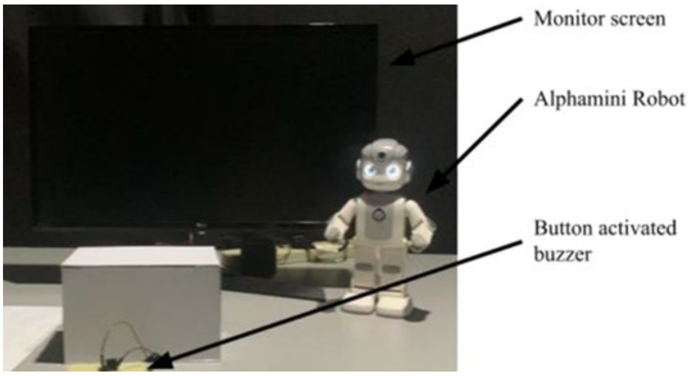

Figure 3. Participants' view

The robot guided participants through each room, describing items, stating challenges, and presenting options to solve them. Regardless of the participant's choice, the robot offered an alternative before repeating the options. This process continued through all eight rooms, with the robot employing high or low controlling language and with or without social praise based on participants' assigned groups.

At the game's end, the robot reminded participants to complete and submit the second questionnaire. Participants signaled completion with the buzzer, and the experimenter thanked them, addressed inquiries, disbursed cash honorariums, and excused the participants. The overall tasks comprised filling out the consent form, completing the first questionnaire, playing the game, and finishing the second questionnaire. The procedure of the experiment is summarized in Figure 4.

2.4 Measures

Table 1. The first set of questionnaires (for pre-experiment and post-experiment)

Adopted from STAI [1]
I feel upset.
I feel uncomfortable.
I feel indecisive (hesitant).
I feel jittery (nervous).
I feel confused.
I feel worried.
I feel upset.

The second questionnaire, a post-experiment adaptation, evaluated participants' responses to the interaction with the robot. This questionnaire encompassed categories such as Usefulness [20], Ease [21], Attitude [7, 22], Liking [23, 24], Intentions [21, 25], Enjoy [22, 25], Beliefs [26-28], and Reactance [29, 30]; adapted from questionnaires used in [11]. All categories, except Reactance [29], were rated on a 7-point Likert scale (one strongly disagrees, seven strongly agrees). The reactance set comprised five statements, with the first four on a 5-point Likert scale and the last measured by the frequency of words representing negative cognitions [31]. Reactance, distinct from stress, denotes explicit aversion to the robot, while STAI reflects participants' emotional displeasure. Compliance was determined by assessing the participants' adherence to the robot's recommendations, quantifying the number of choices they followed as advised by the robot.

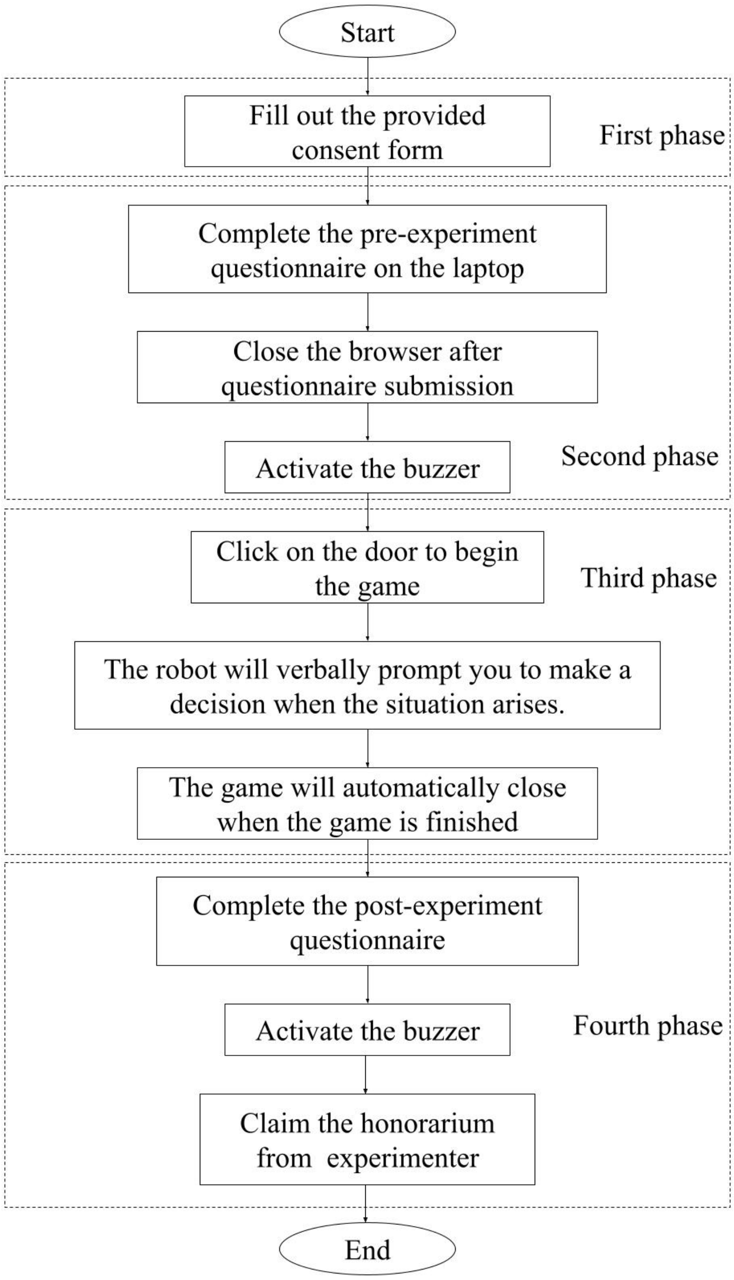

Figure 4. Experimental procedure

3.0 RESULTS AND DISCUSSION

3.1 Participants Exhibit Low Anxiety After Decision-Making Game

Without considering the influence of social cues from the robot, the descriptive analysis indicates that the mean pre-experiment anxiety score (M = 1.761, SD = 0.622) and post-experiment anxiety score (M = 1.467, SD = 0.514) reported by the participants were both lower than the typical population 'normal' anxiety score of 4.0.

Using a one-sample test, the anxiety scores of participants were statistically significantly low by a mean difference of 2.239, 95% CI [2.078 to 2.400] with $t(59) = -27.899$, $p < 0.001$ and by a mean difference of 2.533, 95% CI [2.401 to 2.666] with $t(59) = -38.162$, $p < 0.001$ for both pre and post experiments respectively. This indicates a substantial low in anxiety levels in post-experiment compared to pre-experiment. As such, Hypothesis 1 is accepted. This finding is consistent with the results reported in [34], which similarly concluded that the use of robots in dementia care contributes to alleviating loneliness and anxiety, among other beneficial outcomes.

3.2 Participants Exhibit Positive Social Responses Towards The Interaction With The Social Robot

3.2.1 Reliability Test

The Intraclass Correlation (ICC) Coefficient test, using a two-way random model, revealed a high level of reliability for all measurements in this study. Specifically, for the Pre STAI measurements, the average ICC was 0.847, with a 95% confidence interval of [0.778, 0.900], and an associated F-statistic of $F(59, 295) = 6.542$, indicating a highly significant result with $p < 0.001$. In the case of Post STAI, the ICC was 0.775, with a 95% confidence interval of [0.673, 0.853], and an F-statistic of $F(59, 295) = 4.440$, also indicating a highly significant result with $p < 0.001$.

Moving on to the measurements of Usefulness, the average ICC was 0.680, with a 95% confidence interval ranging from 0.531 to 0.792. The associated F-statistic was $F(59, 236) = 3.120$, demonstrating a highly significant result with $p < 0.001$. Similarly, for the measurements related to Ease, the ICC was 0.718, with a 95% confidence interval of [0.581, 0.819], and an F-statistic of $F(59, 177) = 3.551$, indicating a highly significant result with $p < 0.001$.

In addition, the measurements for Attitude and Intention also displayed significant reliability. For Attitude, the ICC was 0.732, with a 95% confidence interval (CI) of [0.601, 0.828], and an associated F-statistic of $F(59, 177) = 3.731$, with $p < 0.001$. Likewise, for Intention, the ICC was 0.882, with a 95% confidence interval ranging from 0.824 to 0.924, and an F-statistic of $F(59, 177) = 8.443$, indicating a highly significant result with $p < 0.001$.

For Enjoy, the ICC was 0.955, 95% CI [0.933, 0.971] and $F(59, 177) = 22.051$, $p < 0.001$. Moving on to Liking, the average ICC was 0.922 with a 95% CI from 0.889 to 0.948 with $F(59, 708) = 12.767$, $p < 0.001$ while for Belief, the ICC was 0.895, 95% CI [0.849, 0.931] and $F(59, 354) = 9.536$, $p <0.001$. Other than that, the average ICC of Reactance was 0.859 with a 95% confidence interval from 0.789 to 0.910 with $F(53, 212) = 7.070$, $p <0.001$.

These findings demonstrate a strong level of reliability across all response measurements in the study, providing robust support for the validity of the collected data.

3.2.2 Skewness And Kurtosis Analyses

In accordance with Hair et al. (2021) [10], a skewness score falling within the range of -1 to +1 is regarded as highly satisfactory, whereas a score between -2 and +2 is typically deemed acceptable. Scores exceeding the -2 to +2 range are indicative of a significant departure from normality. The standard rule of thumb suggests that when the kurtosis surpasses a value of +2, the distribution is overly peaked. Conversely, when kurtosis falls below -2, it indicates an excessively flat distribution. In cases where both skewness and kurtosis approach zero, the distribution of responses is deemed to follow a normal pattern, which is very unlikely to be found in the real data.

Drawing conclusions from the skewness and kurtosis analyses shown in Table 2, it can be inferred that the majority of responses conform to a normal distribution, with the exception of Post STAI data, which exhibited an excessive peak in its distribution.

Table 2. Skewness and Kurtosis results

Responses	Skewness	Kurtosis
Pre STAI	0.994	0.370
Post STAI	1.634	2.453
Usefulness	-0.111	1.943
Ease	-0.473	-0.380
Attitude	-0.099	-0.991
Intentions	-0.786	1.331
Enjoy	-1.159	0.794
Liking	-0.826	1.346
Beliefs	-0.378	-0.112
Reactance	0.939	0.670

3.2.3 Influences Of Social Cues On Responses: MANOVA And Kruskal Wallis Tests

Post STAI, the next step in the analysis was to assess the impact of social cues on these responses using MANOVA tests. The resultant findings indicated that none of the tested social cues, specifically controlling language and social praises, exerted a noteworthy impact on the participants' responses. In essence, regardless of the particular social cues employed by the robot, the participants consistently displayed uniform responses following the interaction, with minimal variability in their reactions to the assorted social cues scrutinized.

To assess the influence of the social cues on the Post STAI variable, a Kruskal-Wallis test was conducted, and its results mirrored the findings from the other responses. In other words, the participants' reactions remained stable, and there was no significant variation in their Post STAI responses in reaction to the different social cues examined.

In summary, these findings indicate that the utilization of controlling language and social praises by the robot had a limited impact on participants' responses, underscoring the consistency of their reactions across various social cue scenarios. Consequently, the favorable aspects of the MANOVA and Kruskal-Wallis test results led to the subsequent analyses which will delve into examining participants' descriptive responses concerning the social robot as a whole, irrespective of the specific social cues employed.

Overall, Figures 5 and 6 illustrate the descriptive analysis of social responses provided by the participants after interacting with the robot.

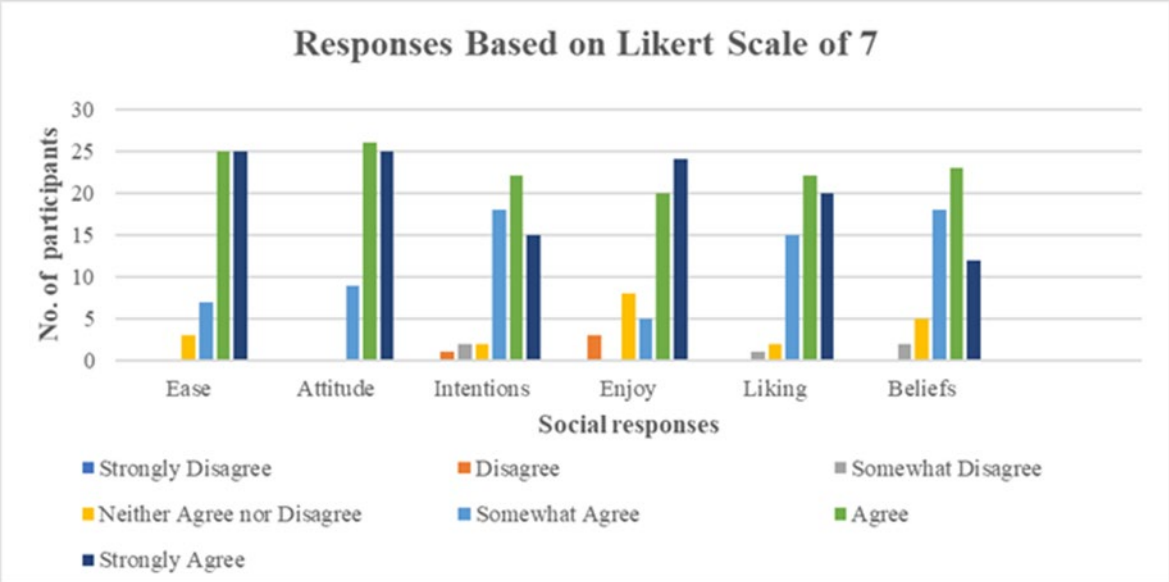

Figure 5. Descriptive analysis for responses with a Likert Scale of 7

The provided percentages offer insights into the distribution of responses across Likert scale categories for various attributes related to social responses toward a social robot (Usefulness, Ease, Attitude, Intentions, Enjoy, Liking, and Beliefs). In terms of Usefulness, a significant portion (51.67%) somewhat agree with the robot's utility, while 26.67% express agreement. Notably, 10% strongly agree, indicating a consensus on the robot's high usefulness. Regarding Ease, there is unanimous agreement (100%) that the robot is not challenging to use, with no respondents expressing any disagreement. Over half of the participants (53.34%) find the robot easy to use, combining both somewhat agree and strongly agree categories.

Concerning Attitude towards using the robot, a unanimous positive attitude is observed, with 85% expressing some degree of agreement. Exploring intentions to use the robot again in the future, a substantial 61.67% express varying degrees of agreement, with 25% strongly agreeing. This indicates a high likelihood of respondents intending to use the robot again. For Enjoy, while a small percentage (18.33%) expresses some form of disagreement or uncertainty about enjoying the robot, a significant majority (73.33%) enjoys interacting with it. Moving on to Liking, the majority (70%) express positive sentiments, with 33.33% strongly agreeing that they like robots. In terms of Beliefs, while 11.66% express some skepticism regarding the robot's advice, a majority of 58.33% agree or strongly agree that they trust the robot. These results offer valuable insights into the robot's acceptance and user satisfaction, paving the way for further exploration and development.

Moving on to the questionnaire with a Likert Scale of 5, a comprehensive analysis of negative sentiments, particularly in relation to Reactance, Pre STAI, and Post STAI measures, provides crucial insights into the nuanced dynamics of human interaction with robotic entities. Regarding Reactance, a significant portion, 20%, strongly disagreed while 48.33% expressed disagreement on the idea of feeling Reactance (angry etc.) toward the robot post-interaction. Turning to the Pre STAI measure, 8.33% strongly disagreed, and the majority, comprising 63.33%, expressed disagreement on feeling anxiety preceding the experimental session. Similarly, the Post STAI measure reveals that 23.33% strongly disagreed, with the highest percentage, 65%, expressing disagreement concerning the experience of anxiety after the experimental interaction. Notably, it is crucial to highlight that no participants reported strong agreement that their interaction with the robot induced feelings of anxiety.

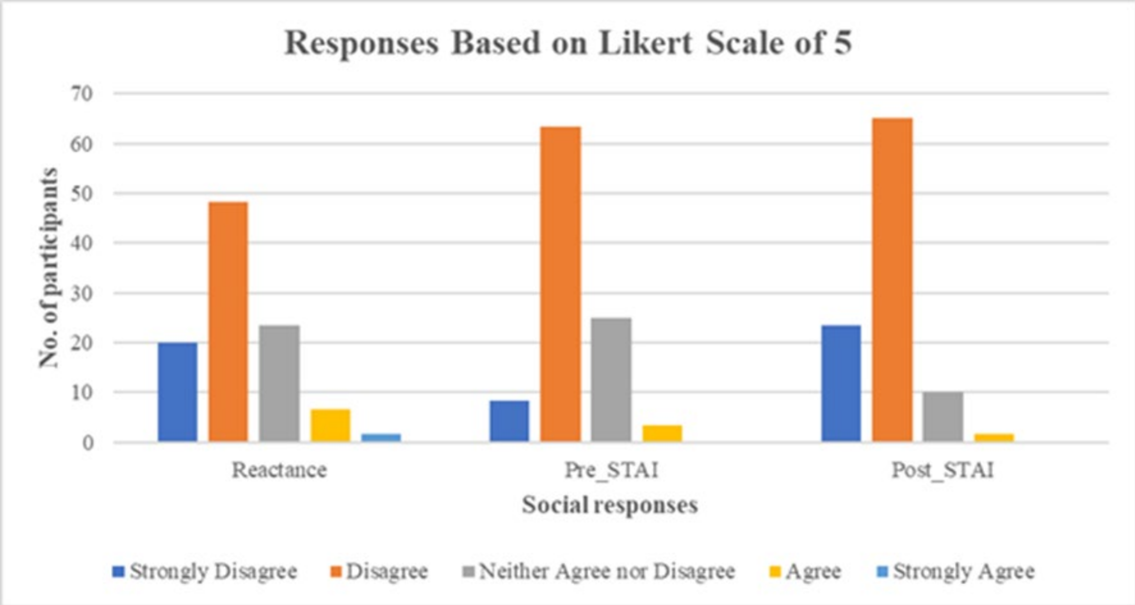

Figure 6. Descriptive analysis for responses with Likert Scale of 5

3.3 Hypothesis 3: Impact Of Social Responses On The Predictive Power of TAM And PRAM

3.3.1 Modelling Based On TAM

To assess convergence validity, the Average Variance Extracted (AVE) has been computed. The generally accepted threshold of AVE is ≥ 0.500. According to the findings presented in Figure 7, all responses met the criterion for data validity, except for the Usefulness.

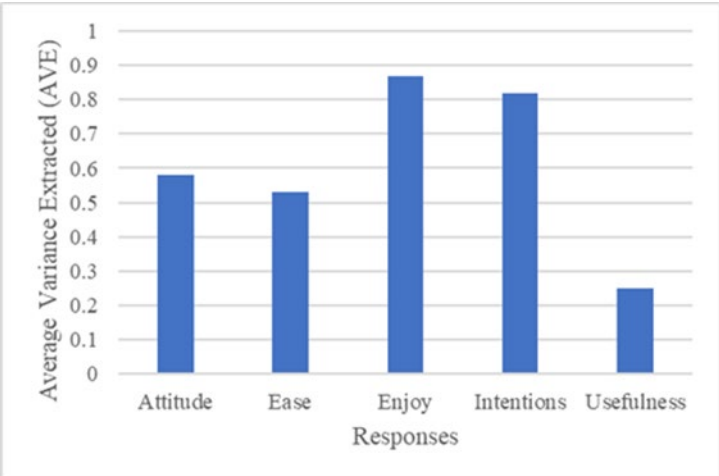

Figure 7. AVE for TAM

Items of Usefulness with factorial loadings below 0.500, specifically variables 1 and 2, were eliminated from the analysis due to their inadequate contribution to the measurement of validity. As a result, the AVE for Usefulness increased to 0.573. Consequently, all AVE values now demonstrate satisfactory results, with each response exceeding the threshold of 0.50.

The consistency values for all responses, measured by Cronbach's α, ranged from 0.712 to 1.000, which is well above the recommended threshold of 0.70. These results affirm that composite reliability was not a concern in this study. For discriminant validity, results showed that all the factorial loads of the items for a response were greater than the other responses. Therefore, the collected data can confidently be asserted as discriminately valid.

According to Ringle et al. (2015) [32], it is recommended that the maximum Value of Variance Inflation Factor (VIF) should not exceed '5.00' to mitigate multicollinearity concerns. In the collected dataset, the VIF values yielded outstanding results, with all cases displaying values lower than 2.00 except for the 2nd, 3rd, and 4th items of Enjoy. After removing those variables, the model did not have any multicollinearity issue as the VIF ranging from 1.000 to 3.746.

As results, Figure 8 shows the structural equation modelling (SEM) of social responses toward the social robot based on original TAM.

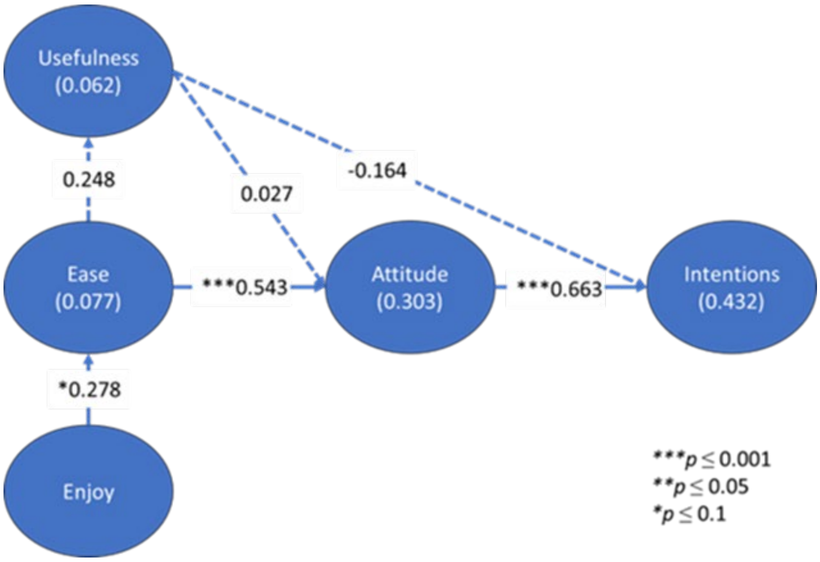

Figure 8. SEM for TAM

Hair et al. [10] proposed that Cohen's effect size values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. Findings indicate a large effect on Ease in predicting Attitude (f2 = 0.40) and Attitude in predicting Intentions (f2 = 0.75). Additionally, there is a small effect of Ease in predicting Usefulness (f2 = 0.07), Enjoy in predicting Ease (f2 = 0.08) and Usefulness in predicting Intentions (f2 = 0.05). In summary, it can be deduced that individuals who derive enjoyment from interacting with the robot tend to feel comfortable using it. This, in turn, fosters a positive attitude towards the robot and cultivates strong intentions to engage with the robot again in the future.

Furthermore, this analysis considered path coefficients for each prediction. To provide a comprehensive view of the Technology Acceptance Model (TAM), the assessment utilized the R2 value, also known as the coefficient of determination, as a metric for judging the quality of the models. The results revealed a satisfactory R2 of 0.43 for Intentions [33].

3.3.2 Modelling Based on PRAM

To establish convergent validity, adjustments were made based on the AVE values, specifically for the responses of Compliance and Usefulness as the AVE values for these responses were less than 0.500 as shown in Figure 9. As such, items with factorial loadings below 0.50 were removed from the analysis for both Compliance, with the exception of Room 4, and Usefulness, where items 3, 4, and 5 were excluded. As a result of these adjustments, the AVE for Compliance increased to 0.710, and for Usefulness, it increased to 0.783. These modifications ensured that all AVE values now demonstrate satisfactory results, with each construct exhibiting values higher than 0.50 in all responses.

Without excluding any items, the Cronbach's α values for all responses exceeded 0.50. The lowest α value was observed for Ease at 0.725, while the highest α value was recorded for Enjoy at 0.956. By utilizing the Fornell-Larcker Criterion to assess the Average Variance Extracted (AVE), the discriminant validity of the data has been confirmed.

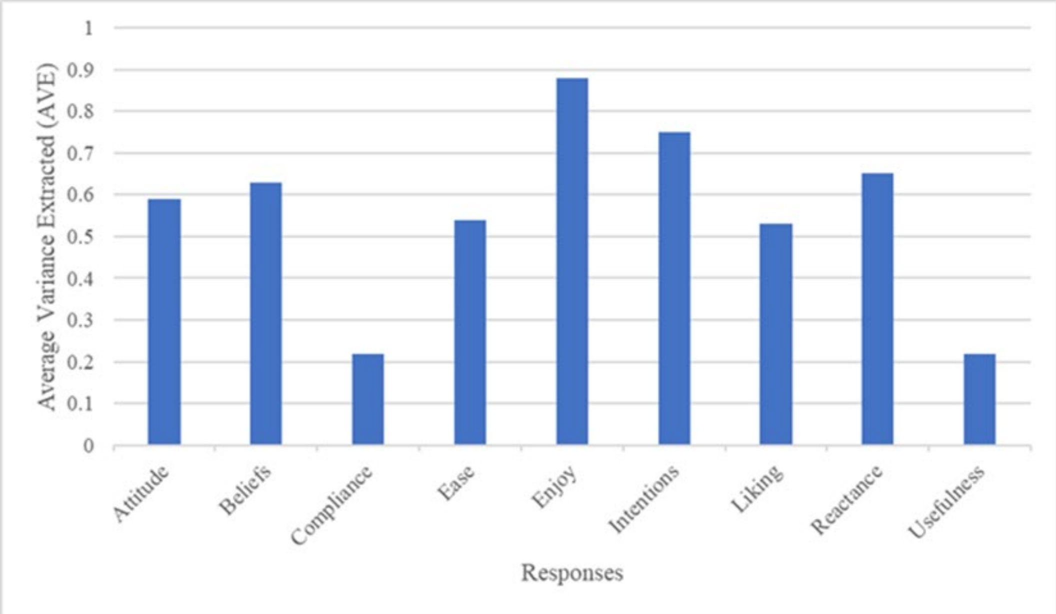

Figure 9. AVE for PRAM

In order to address the issue of multicollinearity, several items were removed from the final model. The removal includes item 5 for Beliefs, items 2, 3, and 4 for Enjoy besides items 2, 9, and 13 for Liking. These adjustments were made to enhance the model's stability and reduce the effects of multicollinearity.

Building on previous research that recommends incorporating social responses when predicting the acceptance of robots [11], Figure 10 illustrates the SEM developed based on responses collected in this study. Also, important to note that for simplicity purposes, all predictions hypothesized in [11] that were found to be statistically insignificant have been omitted from the results below.

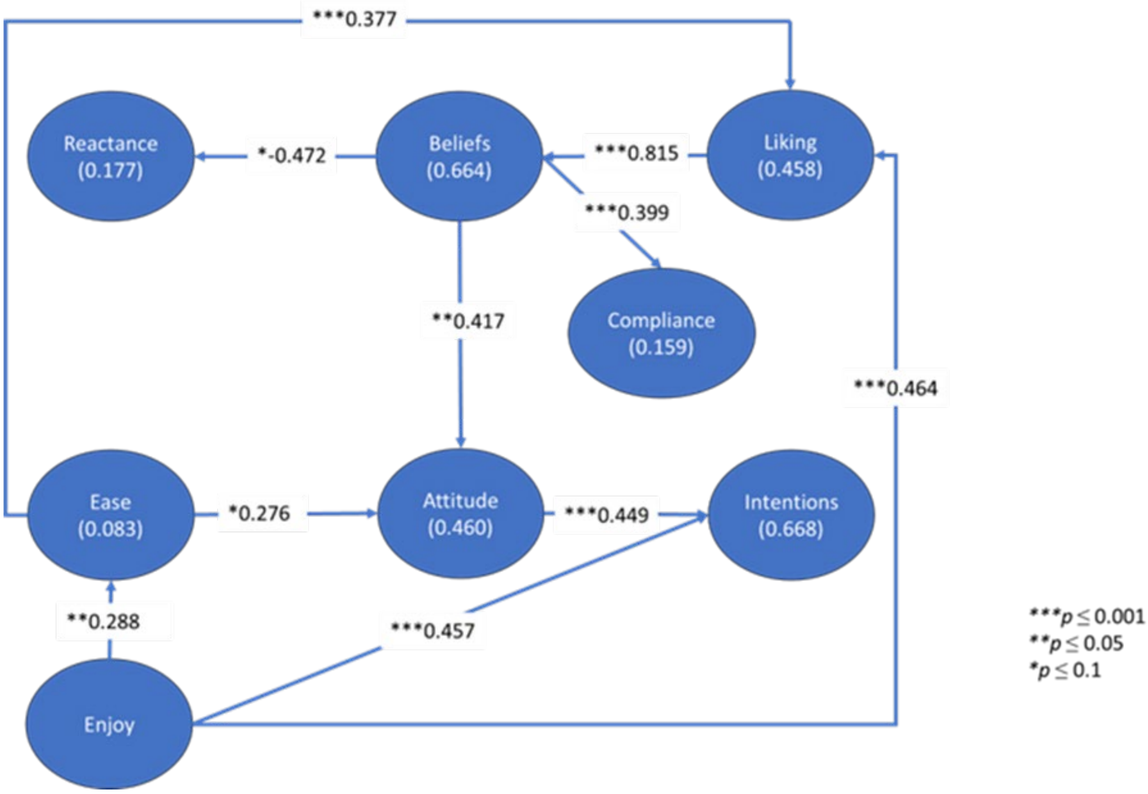

Figure 10. SEM for PRAM

Based on Cohen's effect size [10], large effects were found on Attitude and Enjoy in predicting Intentions (f2 = 0.40 and f2 = 0.41 respectively) besides Enjoy in predicting Liking (f2 = 0.36). There is a medium effect of Beliefs in predicting

Compliance and Attitude (f2 = 0.19 and f2 = 0.15 respectively), besides Ease in predicting Liking (f2 = 0.24). Others like Beliefs in predicting Reactance (f2 = 0.10), Enjoy in predicting Ease (f2 = 0.09) and Usefulness in predicting Intentions (f2 = 0.07) have small effects.

The most prominent path coefficients depicted in Figure 10 indicate that individuals who derive enjoyment from using the robot are likely to develop a liking for the robot. Simultaneously, the ease of use of the robot plays a role in fostering strong beliefs about the robot, leading to a positive attitude towards it and subsequently influencing positive intentions to use the robot again in the future. Another interpretation of the model presented in Figure 6 is that individuals who enjoy interacting with the robot are inclined to express intentions to use the robot again in the future.

This observation is significant because it highlights a notable enhancement in the R2 value for Intentions, specifically by an increase of 0.236 when compared to the Technology Acceptance Model (TAM). In practical terms, this signifies that 66.8% of the variability or changes observed in individuals' intentions can be accounted for or predicted by the inclusion of social responses in the analysis. This improvement underscores the importance of considering social aspects when assessing and understanding individuals' intentions related to the acceptance of robots. The criticality of social robot acceptance lies in its pivotal role in enhancing user engagement, fostering trust in the robot's reliability to fulfill its designated tasks, and facilitating the seamless integration of social robots into users' daily routines, thereby encouraging their sustained adoption [35].

4.0 CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

5.0 CONCLUSION

In summary, the analysis of pre-and post-experiment anxiety scores, conducted without considering the influence of social cues, revealed a substantial decrease in anxiety levels after participants interacted with the robot. Secondly, participants demonstrated consistently positive social responses across various measurements, suggesting that the social robot elicited favorable reactions. The majority of responses indicated agreement with the robot's utility, ease of use, positive attitude, and intentions to use it again, supporting the hypothesis. Consequently, it can be concluded that social robots are a valuable technology for assisting humans in decision-making, garnering positive responses. Lastly, the analysis based on PRAM further emphasized the role of enjoyment, ease of use, and beliefs in influencing attitudes and intentions. The incorporation of social responses in PRAM significantly enhanced predictive power, underscoring the importance of considering social aspects in understanding individuals' intentions related to robot acceptance. Future work might consider running a longitudinal study, as it may offer insights into the long-term impact of HRI on anxiety and social responses.

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