"Feeling Unseen"

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"Feeling Unseen": Exploring the Impact of Adaptive Social Robots on User's Social Agency During Learning

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ABSTRACT

Adaptive robots have the potential to support the overloaded healthcare system by helping new stroke survivors learn about their conditions. However, current adaptive robots often fail to maintain users' engagement during interactions. This study investigated the impact of an adaptive robot on *Social Agency* which has been proposed to influence engagement during learning. Twenty-four healthy subjects participated in a study where they learned about stroke symptoms from a robot providing social cues either 1) when their engagement measured by a Brain-Computer Interface (BCI) decreased or 2) at random intervals. While the results confirmed that Social Agency correlated with Engagement, the robot's adaptive behaviour did not increase Social Agency, Engagement, and Information Recall. Using qualitative methods, we propose that adaptive robots need to explicitly acknowledge users to increase Social Agency.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

Human-Robot Interaction, Brain-Computer Interfaces, Adaptive Social Robots, Engagement, Social Agency, Strokes

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1 INTRODUCTION

Social robots capable of communicating with users can alleviate the burden of strokes on healthcare by aiding new survivors [1, 30]. For example, stroke survivors discharged from hospitals need to learn about symptoms, how to test for them, and rehabilitation techniques [5, 10, 23, 32]. Due to increasing strokes among ageing populations in the EU (1.12 million cases annually) [41], clinicians often could not provide all survivors with the necessary information [26, 27]. Therefore, recent human-robot interaction (HRI) studies supported clinicians with social robots that instructed patients on conditions such as strokes, diabetes, and cancer [1, 28, 31].

While social robots can teach healthy users and patients a variety of topics, they often failed to retain users' *Engagement*, i.e. the cognitive resources users allocated to learning [3, 28, 31, 38]. Lower levels of engagement during learning limited users' *Recall* of information conveyed to them by the robot [2, 14, 38]. Therefore, recent studies investigated adaptive robots monitor users' real-time engagement and re-engage them using social cues [2, 12, 38, 42].

Adaptive robots relied on neurophysiological measures (e.g. brain activity) [3, 37] and behavioural signals (e.g. gaze, gestures and facial expressions) to monitor real-time engagement [11, 14]. Despite the high accuracy of behavioural measures [14, 33], stroke survivors' bodily paralysis may limit these approaches [16, 39, 40]. Therefore, research on stroke patients used Brain-Computer Interfaces (BCIs) to capture electroencephalogram (EEG) signals [7, 9] as a high-temporal resolution measurement of users' engagement through their brain activation [3, 6].

While Szafir and Mutlu [38] showed that a BCI-driven adaptive robot increased both subjective engagement (through questionnaires) and recall from the interaction, other HRI studies observed no such effect despite using similar BCI systems and behaviour design (i.e. social cues) [2, 29]. Additionally, the studies that succeeded in modulating engagement also observed varied results among their participants [18, 38]. Therefore, studies hypothesised that the conflicting results stemmed from a low understanding of how users perceive adaptive behaviour [2, 3, 18, 29, 38].

Adaptive robots' social cues in past HRI studies consisted of beat gestures, raising speech volume, leaning forward, approaching users, and maintaining eye contact [15, 17, 38, 42]. Beat gestures do not carry semantic meaning but can give emphasis to specific words [21]. Although compared to other gesture types (e.g. metaphoric), beat gestures do not reinforce recall [18], they are easier to implement for re-engaging users because they do not rely on the spoken content [12, 38, 42]. For this reason, the majority of HRI studies used beat gestures during storytelling tasks where the robot narrated a story while users listened and then later recalled details of the story [18, 38].

However, recent reviews posited that robots' adaptive behaviour can only re-engage users by also increasing their sense of *social agency*; the users' feeling that their presence influenced the robot's behaviour [22, 35, 43]. Current social cues from adaptive robots (e.g. beat gestures or volume increase) did not explicitly acknowledge users (e.g. asking them if they need a break) for them to recognise their impact on robots' behaviour [19, 36]. In many cases, it remained a question whether users recognised that the robot adapted its behaviour to them [2, 18, 29, 38].

To fill this gap, this study aimed to investigate how adaptive robots would impact users' engagement, recall, and social agency. Moreover, we aimed to investigate the link between engagement and social agency during a robot interaction. Using an EEG-based BCI system, engagement level of healthy users was monitored by a Pepper robot who provided information about stroke symptoms. Subjects interacted with the robot in two conditions, where social cues for re-engagement was either produced adaptively (based on the BCI output) or randomly. Using both self-reported questionnaires and qualitative interviews, we investigated the connections between engagement and social agency as well as whether users could recognise a robot's adaptive behaviour.

2 METHODS

2.1 Participants

Twenty-four healthy university students (mean age=20.5, sd=3.06) participated in this study in exchange for course credits. Of these, 16 identified as female, 7 as male, and 1 as non-binary. Three participants had previous experience with BCIs, 14 with robots, and 9 knew a stroke survivor. All participants signed an informed consent according to the guidelines of the Research Ethics Committee of Tilburg School of Humanities and Digital Sciences.

2.2 Material

This study involved Pepper (Softbank Robotics) which has 20 degrees of freedom allowing for natural gestures. We recorded 9 gestures in Choreographe mainly involving arm movements. Pepper could recognise faces and direct its gaze to people speaking. In this experiment, we asked participants to call out to Pepper before starting the interaction.

To track engagement, we used a passive BCI system similar to Prinsen et al [29]. Our system comprised of a Unicorn Hybrid Black headset (g.tec Medical Engineering, Austria) to collect EEG brain activity and a Simlulink (MATLAB) system for real-time signal processing and classification. The headset included 8 electrodes (Fz, Cz, C3, C4, Pz, Oz, PO7, and PO8) as shown in Figure 1. To monitor engagement, the BCI system extracted the EEG Engagement Index according to Equation 1

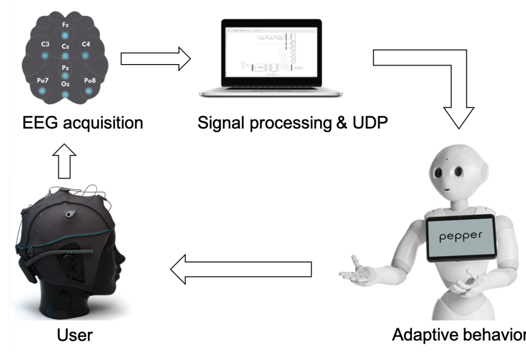

Figure 1: Overview of adaptive human-robot interaction using a passive brain-computer interface (BCI). The BCI system extracted engagement levels from users' EEG signals. When Engagement Index decreased, the robot received a message through User Datagram Protocol (UDP) to generate a gesture.

$$EngagementIndex = \frac{\beta}{\alpha + \theta} \quad (1)$$

where β, α, and θ are the mean signal power in the beta (13-20Hz), alpha (8-12Hz), and theta (4-7Hz) frequency bands averaged over all eight electrodes [4, 13].

To improve the stability of the system, we modified the normalisation technique presented in [29]. Instead of a calibration task at the beginning of the interaction, the system continuously adapted to learners by collecting the Engagement Index over two sliding time windows; a one-minute window as a baseline and a 10-second window as the real-time interaction window. The BCI system continuously compared the Engagement Index in real-time interaction windows to the baseline windows. If the Engagement Index fell below the baseline value, Pepper performed a social cue.

2.3 Procedure

Participants sat 1.5m across from Pepper and received instructions to remain still during the task to avoid producing noise on the EEG signals. The interaction began with a 2 minute practice session where Pepper reminded participants of the study procedure and their participant rights while performing three social cues consisting of leaning forward, raising its voice, and making one of the nine possible beat gestures. The practice session aimed to familiarise participants with Pepper's voice, movements, and social cues.

The study followed a within-subjects design where users interacted with Pepper under two conditions; Adaptive vs. Random. In both conditions, participants wore an EEG cap while listening to Pepper present stroke-related information. In the Adaptive condition, Pepper generated social cues when participants' engagement decreased below our threshold while the Random condition had Pepper produce social cues at random times. Each condition lasted 10 minutes in which Pepper described either the physical or cognitive symptoms of a stroke. We counterbalanced both the conditions and the narratives. Pepper maintained eye contact for the whole duration of the interaction. While we informed participants that

Table 1: Post-task questionnaire items.

Measure	Construct	Question
Social Agency	Interactivity	I impacted the robot's behaviour The robot changed its behaviour for me
	Autonomy	The robot decided its own behaviour I felt uninvolved in the interaction
	Adaptability	The robot aimed to help me learn The robot behaved to help me
Engagement	Attention	I paid attention to the robot I was focused on learning
	Usability	I felt frustrated during the interaction Interacting with the robot was demanding
	Reward	Interacting with the robot was engaging Interacting with the robot incited my curiosity

Pepper changed behaviours between conditions, we did not inform them of the difference until the end of interview.

2.4 Evaluation

After each condition, participants filled a questionnaire measuring their social agency (6 items) and engagement (6 items) on a 5-point Likert scale (see Table 1). We developed the questionnaire using Jackson et al.'s [19] description of social agency during robot interaction. The engagement items came from O'Brien's engagement questionnaire [25]. Following the questionnaire, participants answered 10 multiple choice questions about the information they learned in the condition. Finally, we conducted semi-structured interviews with participants in which they explained their answers in the questionnaires and whether they could guess the difference between conditions. We analysed the interview transcripts using Braune and clarke's description of thematic analysis [8].

3 RESULTS

3.1 Self-reported questionnaire

Participants' engagement in the Adaptive and Random conditions did not differ (p=0.66), nor did their social agency (p=0.8, see Table 2 for an overview). However, engagement correlated with social agency (r=0.56, p<0.001) and predicted (β=0.5, p<0.001) 30% of its variance in a linear model (Figure 2A). Specifically, social agency correlated with engagement constructs of reward (r=0.75, p<0.001) and usability (r=0.34, p=0.01) but not attention (p=0.52). When removing attention from the model, reward (β=0.44, p<0.001) predicted 55% of social agency's variance (R^2=0.54, F(1, 46)=28.44, p<0.001) while usability did not contribute to the prediction (p=0.77).

3.2 Information recall

Participants' scores on the post-interaction tests did not differ (p=0.83) between the Adaptive and Random conditions (see Table 2). Additionally, while recall did not differ between the topics of physical and cognitive symptoms (p=0.38), participants recalled less information (V=226, p=0.001) in the second interaction (M=4.08, SD=1.95) compared to the first one (M=6.33, SD=1.95) regardless of condition. While social agency did not correlate with recall (p=0.7), engagement did correlate (r=0.35, p=0.01) and predict (β=1.22, p=0.014) 10% of variance in recall (R^2=0.10, F(1, 46)=6.42, p=0.014). Adding social agency (β=-1.7, p=0.002) and order of condition (β=-2.3, p<0.001) to engagement (β=1.88, p<0.014) improved the performance of the model by predicting 46% of recall variance (R^2=0.46, F(1, 46)=14.24, p=0.014) seen in Figure 2B.

3.3 Interviews

Only few participants (7/24) understood that conditions differed in that one entailed robot behaviour adapting to their engagement while the other included randomised social cues. Of these participants, only 2 correctly identified the Adaptive condition while the other 5 attributed the conditions in the wrong order. Most participants (17/24) did not distinguish between conditions and rated their Engagement and Social Agency similarly in both conditions.

While many participants (20/24) suspected that Pepper monitored their engagement and used social cues to re-engage them, they felt unsure due to the lack of explicit acknowledgement: *"It should say something like "Hey, I noticed you're getting tired" and comfort me. That's what a real teacher does" (P3).* Of these participants, most (16/24) felt engaged due to feeling social agency in the interaction. In contrast, the rest (4/24) felt frustrated as they felt unable to influence the interaction and provided low engagement, social agency, and attention ratings. When asked how Pepper could increase their social agency, most participants (21/24) needed explicit acknowledgement without which they (19/24) felt ignored and uninvolved regardless of whether Pepper adapted to their engagement: *"I felt unseen. If I left the room Pepper would just keep going. I felt like there was no understanding on the other side." (P10).* Additionally, many participants (17/24) suggested that Pepper should not only address their presence but also involve them by asking for feedback instead of continuously speaking. Asking for feedback can increase social agency through conversation which create social obligation: *"Pepper doesn't do something different for me, it's programmed to say something. If it asked me for feedback, I would be part of the conversation. It wouldn't feel like a monologue." (P7).*

4 DISCUSSION

This study explored the impact of adaptive robot behaviour on users' engagement, social agency, and information recall during a healthcare-related HRI learning task. Using an EEG-based BCI system, a Pepper robot monitored participants' brain activity and provided social cues when their engagement decreased. The results showed no effect of adaptive behaviour on neither participants' perception of the interaction nor their recall. Our interviews revealed that the majority of the participants could not tell in which condition the robot adapted its behaviour to their engagement level which supports previous theories on user's social agency [22, 35, 43].

Despite using similar EEG engagement classification and robot social cues, our results run counter to that of Szafir and Mutlu [38] who showed that adaptive robot behaviour increased recall compared to random behaviour. The differences between task difficulties could explain this misalignment. Similar to the storytelling task in Szafir and Mutlu [38], our task lasted 10 minutes but contained more difficult information which yielded lower recall as noted by our participants. On the other hand, our results align with Huang and Mutlu's [18] 6-minute interaction containing complex domain information and similarly found that robots' beat gestures yielded no impact on recall. Our subjects likely experienced mental fatigue due to continuous delivery of stroke information by the robot and

Table 2: Summary of questionnaire outcomes. Means and (SDs) given for each measure and their corresponding constructs.

	Social Agency	Interactivity	Autonomy	Adaptability	**Engagement**	Attention	Usability	Reward	**Recall**
Adaptive	3.11 (0.52)	2.21 (1.05)	2.85 (0.94)	4.27 (0.63)	3.49 (0.63)	4.02 (0.83)	2.94 (0.84)	3.52 (0.95)	5.25 (2.21)
Random	3.12 (0.6)	2.21 (1.02)	2.85 (0.83)	4.31 (0.72)	3.47 (0.63)	4.02 (0.71)	3.04 (0.72)	3.33 (0.97)	5.17 (2.16)

Figure 2: Regression plots between A) Social Agency and Engagement based on the condition type, and B) recall and Engagement based on the condition order.

lost interest in robot behaviour during the task. Previous studies without robots support this as increased difficulty of learning tasks lowered participants' engagement due to fatigue [24, 34].

While the quantitative results did not explain why the adaptive condition did not increase participants' engagement and recall, our qualitative analysis suggested that participants felt frustrated or ignored due to Pepper's inability to address them explicitly. Past reviews hypothesised that this lack of social agency impedes the effectiveness of adaptive robots [19, 22, 36]. However, interrupting teaching tasks to address users may distract them and lower their ability to learn as seen in previous studies [20]. Therefore, future research should aim to explore how adaptive robots can explicitly acknowledge users without disrupting learning. For example, Alimardani et al. [2] found that subjective engagement increased when a robot performed gestures as feedback for users reciting newly learned foreign words compared to a robot that made no gestures. While initially unclear why Alimardani et al's gestures increased subjective engagement, our study supports their hypothesis that gestures given as feedback contained explicit acknowledgement to users' performance which raised their social agency.

While social agency correlated with engagement and predicted recall, it did not correlate with Recall directly. Therefore, we provided evidence for our and previous literature's [19, 22, 36] hypothesis that Social Agency impacts Engagement but impacts Recall only indirectly. Participants' feelings of being ignored by Pepper coupled with the difficulty of the task could provide an explanation for why we observed no connection between Social Agency and recall. Therefore, future studies should investigate whether adding explicit acknowledgement increases social agency. In our future work we will validate our engagement classification and investigate whether our objective measurements of engagement correlate to the measures of Social Agency, Engagement, and Recall.

5 CONCLUSION

Using implicit social cues of gestures, voice raising, and posture changes, our adaptive robot did not increase users' Social Agency when adapting to their engagement compared to randomly timed behaviour. However, higher experience of social agency contributed to users' higher levels of engagement while learning and indirectly increased their recall. Our use of interviews and qualitative data which currently remain underused in HRI research provided us insights to explain these findings and propose suggestions for future research. Users need explicit acknowledgement of their self-induced impacts on interactions to increase their social agency. In the future, we plan to expand these results by designing adaptive robot behaviour using explicit social cues and consequently investigating the effectiveness of such design on user experience and performance during robot-assisted learning.

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