A Robot-Led Intervention for Emotion Regulation: From Expression to Reappraisal

Guy Laban[1,*], Julie Wang[2], Hatice Gunes[3]

***Abstract*—Emotion regulation (ER) is a crucial skill for managing emotions in everyday life, yet finding a constructive and accessible method to practice ER remains challenging due to cognitive demands. In this study, we explore how regular interactions with a social robot, conducted in a structured yet familiar environment within university halls and departments, can provide effective support for practising ER via cognitive reappraisal. Twenty-one students participated in a five-session study at a university hall or department in the UK, where the robot (QTrobot, LuxAI), powered by a large language model (GPT 3.5) facilitated structured conversations, encouraging the students to reinterpret emotionally charged situations that they shared with the robot. Quantitative and qualitative results indicate significant improvements in ER, with participants reporting better understanding and control of their emotions, significant changes in constructive ER tendencies and positive effects on mood and sentiment after each session. The findings also demonstrate that repeated interactions with the robot encouraged greater emotional expression, including longer speech disclosures, increased use of affective language, and heightened facial arousal. Notably, expression peaked during key reappraisal moments, particularly when participants were prompted to reinterpret negative experiences. The qualitative feedback further highlighted how the robot fostered introspection and provided a supportive space for discussing emotions, enabling participants to confront long-avoided emotional challenges. These findings demonstrate the potential of robots to effectively assist in ER in familiar environments, offering both emotional support and cognitive guidance.**

***Index Terms*—Human–Robot Interaction, Emotion Regulation, Cognitive Reappraisal, Well-being, Longitudinal, Large Language Models**

I. Introduction

University students face significant emotional challenges as they balance academic pressures, personal growth, and social expectations [1]. These challenges can result in heightened stress, anxiety, and emotional turmoil, making it difficult for students to manage their emotions effectively [2]. Without practising *emotion regulation* (ER), these emotional experiences can negatively impact their well-being, academic performance [3], and overall mental health [4]. ER, a set of processes, strategies and techniques involving the monitoring, assessment, and modification of one's state, behaviour, or cognition in a given situation, serves as a vital means of coping with emotional distress and its associated comorbidities [5]. These strategies can be either constructive or maladaptive [6]–[9]. Constructive strategies require more cognitive effort, making them harder to consistently apply [10], [11]. Hence, introducing individuals to constructive ER skills at a preventive stage is crucial, as it is suggested that when experiencing poor mental health, people tend to adopt maladaptive strategies that perpetuate negative emotional interpretations [12]. Traditional methods for training and facilitating ER, such as therapy or peer support, can be effective but are often limited by availability, cost, and accessibility [13], especially in high-pressure academic environments [3].

Social robots, machines that are aimed at interacting socially with humans [14], offer an on-site, consistent alternative that can provide round-the-clock, personalised emotional support to many users in the same facility. The non-judgmental and objective nature of robots can create a safe socio-emotional space for individuals to express their feelings openly [15]. Due to social robots' ability to establish rapport [16], [17], prior research has shown that robots can engage users in meaningful social interactions [15] for supporting well-being [18], [19]. By integrating into students' everyday routines, robots could help bridge gaps in access to emotional regulation tools, making support more readily available and continuous. It can reduce the cognitive and emotional barriers that often prevent young individuals from seeking help [20] and encourage them to discuss their problems openly. Here, we are specifically interested in the robot's ability to deliver interventions supporting students' *cognitive reappraisal*, a constrictive ER strategy aimed at changing the way one interprets emotionally charged situations to reduce their negative impact [21], with direct and long-term impact on well-being [22]. However, it requires substantial cognitive effort to consistently apply, particularly in stressful situations [11], [23]. By mediating this process, social robots can provide external guidance, helping students engage in reappraisal more effectively. The robot's conversational support could ease the cognitive demands by prompting reflection, offering new perspectives, while providing space for talking about their emotions [15], making it easier for students to integrate this crucial skill into their everyday lives.

In this paper, we present the *first study* exploring how regular interactions with a conversational social robot in familiar environments can support emotional understanding and improve ER and expression through cognitive reappraisal. Twenty-one university students participated in a multi-session study including five sessions talking with a robot, designed

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to facilitate cognitive reappraisal intervention. The sessions took place in settings familiar to the participants, such as their university campus, to maintain ecological validity. Each session, scheduled at the participant's convenience via an app, focused on key aspects of well-being, and the robot engaged participants in structured conversations aimed at prompting cognitive reappraisal. The robot utilised a large language model (LLM) to process participants' responses and provide supportive, reflective feedback. We collected quantitative data using standardized questionnaires and qualitative data from in-person semi-structured interviews, employing a mixed-methods approach to gain a comprehensive understanding of how robot-mediated cognitive reappraisal influences students' emotional understanding, regulation strategies, and overall well-being over time. In addition to self-report measures and qualitative interviews, we analysed the interaction logs and videos to capture verbal expression (e.g., what participants said and how they said it) and facial expression cues (participants' nonverbal emotional displays) during the sessions. This multimodal data provided objective indicators of participants' emotional engagement and expression throughout the intervention.

II. Related works

A. Affective Reasoning in AI

Recent work shows that LLMs are exhibiting some extent of measurable *emotional understanding*, the ability to recognise, interpret, and even reason about human affect. Tak and Gratch [24] found that GPT-4 predicts emotional appraisals and valence effectively but has difficulty with emotional intensity and coping strategies. Mehra et al. [25] evaluated the ability of LLMs to explain facial expressions based on valence and arousal values, finding that the models achieve high semantic similarity scores when describing emotional facial expressions in semantic terms. Taken together, these findings indicate that state-of-the-art LLMs now provide a credible substrate for affect-aware applications. Due to these recent advances in AI, previous studies have evaluated LLM capacity for ER. For example, Zhan et al. [26] demonstrated that by employing expert-informed reappraisal frameworks, LLMs can generate targeted cognitive reappraisals that outperform human responses in empathy and effectiveness. Similarly, Li et al. [27] found that GPT-4 surpasses human re-appraisers in dimensions such as effectiveness, empathy, and novelty, with the performance gap driven primarily by intrinsic skill rather than effort.

B. Social Robots Supporting ER and Well-Being

Research on social robots for ER is still in its early stages, but recent studies provide promising insights into their potential to enhance emotional well-being in various settings. Long-term interactions with a social robot showed that it can foster increased self-disclosure over time via affect labeling (see [28]), supporting emotional well-being. Participants disclosed more to the robot over time, while perceiving themselves as being more open [29]. A replication of this study deployed a social robot as an intervention for informal caregivers experiencing emotional distress. It found that caregivers benefited from self-disclosure to the robot, becoming more accepting of their caregiving role while reporting improved mood and reduced feelings of loneliness [30]. Another study examined teleoperated social robots used for mindfulness, demonstrating their positive impact on relaxation over time [31].

C. Social Robots Supporting Young Adults and Students

Young adults and students who face unique emotional challenges could benefit from social robots designed specifically to meet their emotional needs [32]. A study on artificial agents supporting student well-being found that university students experience significant stress in social situations like public speaking and group discussions. Animal-like robots and conversational agents were seen as helpful for managing anxiety, highlighting their potential for addressing mental health challenges [33]. Non-conversational socially assistive robot (Purrble) was introduced to highly anxious university students as in situ emotional support tools. It demonstrated positive effects, reducing anxiety symptoms and improving students' ER self-efficacy [34]. However, due to Purrble's pet-like embodiment, the robot's role was primarily focused on providing companionship rather than offering guidance for reappraising emotions. Robinson et al. [35] trailed a humanoid robot delivering brief mindfulness breathing technique to students experiencing psychological distress, enhancing relaxation, contentment, and engagement. Another study investigated the use of robotic positive psychology coaches at a university campus. The robot delivered personalised interventions through rapport-building techniques over a series of interactions supporting students' well-being [36].

III. Research Questions

Previous studies have highlighted the potential of robots to support well-being (see Section II). However, no research has focused on how social robots can encourage constructive ER strategies, particularly in familiar settings where they communicate appropriately using LLM. Most interactions aimed at supporting well-being view the robot as a companion (e.g., [37]), rather than an active guide in helping people navigate and manage their emotions. Here, we focus on how regular interactions with a robot in familiar environments can support and improve ER. Therefore, this study investigates how a robot-mediated cognitive reappraisal intervention integrated into familiar settings, can help participants process their emotions more effectively, adopt constructive ER strategies, and experience emotional upliftment. Beyond demonstrating how robots influence people's well-being, our study seeks to investigate if robots can help individuals change the way they perceive and approach emotionally charged situations, potentially improving their ability to cope in the future.

Accordingly, we pose three research questions. First, we aim to assess the robot's role in supporting participants' self-regulatory mechanisms of ER, specifically in understanding emotional experiences and feeling in control. Thus, we ask **(RQ1)**: *To what extent does interacting with a robot influence students' ability to understand and control their emotions?* Next, we assess whether the cognitive reappraisal intervention

facilitated by the robot supports the cognitive adaptation of constructive ER tendencies. Therefore, we ask **(RQ2)**: *To what extent does interacting with the robot during cognitive reappraisal interventions help students reframe negative emotional experiences and adopt constructive ER strategies?* Beyond addressing the effects of cognitive reappraisal on internal emotional processing, we further explore how repeated interactions with the robot influence participants' outward emotional expressions. Specifically, we examine whether verbal and facial emotional expression change over time and across individual interactions, as behavioural cues of ER. Thus, we ask **(RQ3)**: *To what extent does interacting with a robot affect verbal and facial emotional expression over time and throughout each interaction?* This research question aims to determine whether participants become more verbally expressive (e.g., speaking for longer, using more emotion-descriptive words, or displaying changes in the sentiment of their disclosures) and whether their facial expressions systematically shift in arousal or valence during the intervention. Finally, given the direct benefits of cognitive reappraisal to emotional well-being, we evaluate the impact of the intervention on participants' moods and feelings. Hence, our final research question is **(RQ4)**: *To what extent do robot-assisted cognitive reappraisal impact students' well-being and emotional upliftment?*

IV. The Study

A. Setup

The study was conducted in two cohorts. In cohort 1 (C1), it took place in a dedicated room within university halls (Trinity Halls, University of Cambridge, UK) where students live, study, and spend much of their time. In cohort 2 (C2), the study was conducted in a designated room within a university department at the University of Cambridge that students routinely attend for academic purposes. In this setting as well, the robot was placed in an environment where students work, study, and spend most of their day. In both locations, students attended the sessions as part of their daily schedule within these environments. Participants sat on a couch positioned in front of the robot, which was placed on a low table to match the participants' eye level. An external video camera was positioned behind the robot, and an external microphone in front of it (see Figure 1).

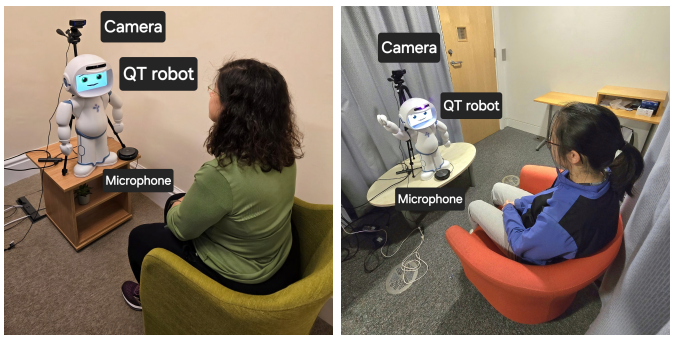


Fig. 1: The deployment settings. On the left - C1; On the right - C2.

B. Participants

An *a priori* power analysis was conducted for a linear mixed-effects model [38] with a single group with 5 repeated measurements per participant to determine the required sample size. The analysis assumed an effect size of f = .25, an α error probability of .05, and a desired power (1 - β) of .80. The correlation among repeated measures was set at .5, and ϵ was assumed to be 1. The power analysis indicated that a sample size of 21 participants would be sufficient to achieve the desired power. The analysis yielded a λ of 13.13, a critical F-value of 2.49, and 4 numerator and 80 denominator degrees of freedom. The actual power achieved was .82.

Participants were required to be either residents or students affiliated with Trinity Hall (C1) or students of the department in which the study took place (C2), to maintain the experience of participating in a familiar environment. All participants were required to be fluent in English. To ensure safety, we screened for individuals exceeding clinical thresholds for severe depression (PHQ-9 $>$ 19) or severe anxiety (GAD-7 $>$ 14), with none of the subjects meeting the exclusion criteria.

Accordingly, we recruited 21 participants on a voluntary basis. Participants were recruited in two cohorts: one cohort of students from university halls (Trinity Hall, University of Cambridge; C1) and an additional cohort of students from a university department (C2). Recruitment for C1 was facilitated through posters displayed around the hall's premises and the hall's social media channel on Instagram and online listings. Recruitment for C2 was facilitated through a single email call for participants. The same description was used across posters, emails, and online listings to ensure consistency and transparency. This recruitment approach was approved by the relevant contacts and ensured that the study was presented consistently across cohorts, with a clear and transparent description provided in all participant-facing materials. Participants were not financially compensated and took part voluntarily after being fully informed about the study's purpose and procedure. In both cohorts, students attended the sessions as part of their daily schedule within these environments. Participants ranged in age from 18 to 27 (M = 20.62, $\pm$2.66), with 43% identifying as female, and more than 50% being native English speakers. The University requires a minimum score of 7.5 on the IELTS exam, ensuring that all participants possess a sufficient level of English proficiency. More than 70% of participants were undergraduate students. The remaining participants included postgraduate students (e.g., master's and MPhil students) who were affiliated with the university departments or resided in Trinity Hall where the study was conducted. 42.11% of the participants were from STEM departments, 36.84% from the social sciences, and 21.05% from the humanities.

C. Robotic platform & System

We selected the QTrobot (referred to as QT) by LuxAI S.p.A as the robotic platform to deliver the intervention. QT features a screen face, an RGB-D camera, and a microphone array. It is a 90 cm tall, child-like robot with a 2 DOF neck, 4 DOF arms (including shoulders, elbows, and hands), and static legs. We selected the QT for this study as it offers an

approachable humanoid interface that encourages conversational interactions without eliciting uncanny perceptions (as demonstrated by previous studies using QT, e.g., [39]–[42]). Additionally, it allows for smooth integration of the LLM with the system's components, ensuring precise voice synchronisation and efficient user input processing. We used an open-source system [43] (with turned-off adaptation functionality to avoid confounding effects) to develop and implement the LLM-powered (GPT 3.5) intervention described in Section IV-E and Figure 3. We used AWS Polly's Amy synthesised voice and synchronised the robot's mouth movements with the spoken voice using Amazon Polly visemes. Participants' speech was captured using Google Cloud Speech-to-Text and submitted directly to the OpenAI API. The robot's motors were used to wave hello and goodbye.



Fig. 2: Illustration of part of the interaction structure within each session, demonstrating participants' responses to a Positive-Connotation Question (PCQ) sequence and the Cognitive Reappraisal (CR) process prompted by the robot. The robot's response is generated via an LLM pipeline, integrating earlier positive disclosures to guide reappraisal and encourage reflection.

D. Ethics and Safety

The study was approved by the department's ethics committee, and all participants signed an informed consent and were debriefed after their participation. To ensure that the LLM-powered interactions follow appropriate safety guidelines, the robotic system used in this study incorporates safety measures such as an integrated content moderation layer to filter inappropriate inputs, rigorous adversarial testing to validate response robustness, and prompt engineering techniques to constrain the topic and tone, all embedded within a structured conversational framework and guided by comprehensive ethical oversight (see [43]). To test these measures, we simulated various scenarios and conducted pilots with the university hall's well-being team prior to the study, ensuring that the system was performing in line with their expectations (see Section IV-E4). Participants' average scores of PHQ-9 [44] and GAD-7 [45] indicated mild to moderate symptoms (PHQ-9: $M = 7.19$, $SD = 3.84$; GAD-7: $M = 6.33$, $SD = 3.51$), suggesting the sample was broadly suitable for a preventive, non-clinical intervention. To protect participants' privacy, sessions were conducted in private, closed-door spaces, without human supervision. These measures were discussed with participants during consent and debriefing. All data were anonymized and processed automatically.

E. Experimental Design and Intervention

1) Experimental Design: We conducted a multi-session longitudinal study using a single-condition, repeated-measures experimental design. The study was approved by the departmental ethics committee. Participants interacted with the robot QT over five sessions within two weeks. The intervention was based on the PERMA model [46], [47], a positive psychology framework designed to capture the multidimensional aspects of well-being: **P**ositive Emotions (session 1), **E**ngagement (session 2), **R**elationships (session 3), **M**eaning in Life (session 4), and **A**ccomplishments (session 5). PERMA model is a valuable framework for structuring well-being interventions by addressing key dimensions of positive psychology [48], [49]. This five-session structure was selected to align with the five pillars of the PERMA model and to ensure the intervention remained manageable within students' routines. The pilot phase (see Section IV-E4) confirmed that five sessions provided meaningful exposure without overburdening participants. The goal of the intervention was to elicit cognitive reappraisal, helping participants to change their subjective interpretation of emotional stimuli [21].

2) Theoretical and Strategic Framing of the Intervention: Applying Slovak et al. [50] framework to our intervention helps position our approach more precisely within the landscape of ER interventions. Our robot-led intervention targets the *implementation stage* (i.e., helping participants apply a specific ER strategy) of Gross's Process Model of ER [5] and specifically supports *cognitive change* (i.e., changing the interpretation of an emotional event), in particular, via guided reappraisal. Strategically, the intervention is best described as *experiential* (i.e., focusing on learning through emotional engagement rather than instruction) and *offline* (i.e., delivered outside of real-time emotionally stressful events), offering participants structured, repeated opportunities to engage with emotionally meaningful content in a safe environment. Rather than intervening in the moment of emotional distress, the robot scaffolds the development of ER skills through dialogue-based reflection. At the implementation level, our design aims to facilitate both expression and reinterpretation.

3) The Intervention's Pipeline: To achieve this, QT facilitated the intervention in a structured manner (see Figure 3). Each interaction began with pre-scripted greetings, followed by QT asking a pre-scripted, positive connotation question (**PCQn**) about one of the PERMA topics, corresponding to the session number (e.g., "*Who do you feel closest to in your life right now, and why?*"). After the participant responded, their response was submitted to GPT-3.5 with the prompt, "*Follow up on what I just shared with you*" (**Fn**), generating a follow-up question. After the participant responded again, all of their responses were resubmitted to GPT-3.5 with the prompt, "*Recognise the feelings and emotions I shared with you and ask me if I am ready for another question*" (**Rn**), to prepare the participant to move on in the conversation. In line with previous studies examining LLMs' ability to recognise and appraise emotions from disclosures (e.g., [24]), this segment of the interaction was designed to facilitate emotional reflection and summarise the interaction before proceeding. Further, this

process (PCQn to Rn, see Figure 3) occurred twice (i.e., asking an additional pre-scripted positive connotation question, e.g., "*Can you share a memorable moment you recently had with a friend or family member?*"), with questions framed around the same PERMA topic.

Following this procedure QT asked the participant one pre-scripted, negative connotation question (**NCQ**) about the session's PERMA topic, encouraging the participant to reflect on a challenge they might be experiencing in a central area of their life (e.g., "*Do you ever feel lonely or misunderstood in your relationships?*"). Rather than following up directly on the participant's answer, QT aimed to guide them through reappraising their negative experiences or emotions by reintroducing relevant elements from their earlier responses to the positive connotation questions To facilitate this, the participant's response was submitted to GPT-3.5 with the prompt "*Help me to see the positive aspects of the negative experience I shared with you, and assist me in cognitive reappraisal by highlighting the positive elements from my previous responses. Then, ask me a question that will encourage self-reflection*" (**CR**). After the participant responded, their answer was submitted again to GPT-3.5 with the prompt, "*Follow up on what I just shared with you*" (**F3**), to engage them further in discussing their reappraised feelings. After the participant responded, the robot ended the session with a pre-scripted message, thanking the participant and wishing them well. See supplementary material 1 for all interaction items, Figure 2 for a simplified illustration, and supplementary material 2 for an illustrated example of a full transcript.

4) Pilot Validation: Before starting the main experiment, we conducted a short validation pilot with five students and two well-being advisors affiliated with the university halls. Each of the seven participants engaged in a full session with QT. Following each session, we conducted a brief structured interview to qualitatively evaluate the reappraisal responses generated by the robot. Specifically, participants were asked whether QT had acknowledged their negative experience, offered a perspective that encouraged reinterpretation, and integrated earlier responses in a way that felt helpful or meaningful. All participants confirmed that QT's responses achieved these aims, and described the reappraisal segment as natural, reflective, and emotionally appropriate. The two well-being advisors independently evaluated their sessions and highlighted that QT's strategy was aligned with principles commonly used in their own practice. They affirmed that the tone, structure, and scope of QT's responses were suitable for the intervention. To complement this qualitative feedback, we manually reviewed all LLM-generated responses from the pilot sessions, confirming that each aligned with cognitive reappraisal goals.

F. Procedure and Measures

Students scheduled their participation (first session) using a Calendly page with information about the study. Upon attending the first session, participants were given further instructions and explanations about the study through an informed consent form, which they were required to sign

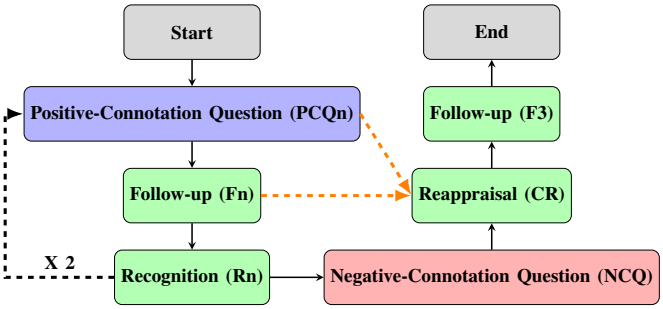


Fig. 3: The interaction flow. The blue block indicates pre-scripted Positive-Connotation Questions (PCQn), while the Red block represents the pre-scripted Negative-Connotation Question (NCQ). Green blocks involve responses powered by the LLM - Follow-up (Fn), Recognition (Rn), and Reappraisal (CR). The split arrow from Rn to PCQn suggests repetition (x2). The orange split arrow shows that CR is based on PCQn and Fn responses.

before participating. Before interacting with QT for the first time, participants completed the Short Cognitive ER Scale (Short-CERQ [51]; M = 3.38, $\pm$.48, α = .83) reporting their ER tendencies, and also several demographic values (age, identified gender, biological sex, nationality, first language).

Before starting each session, participants reported their mood using the 12-item Immediate Mood Scaler (IMS-12 [52]; M = 4.72, $\pm$.93, α = .92) and described their emotions and feelings in one word using a text box (1WEpre). Before the first interaction, participants were given basic instructions about their interactions with QT and its functionalities. Once participants indicated they were ready to begin, the experimenter left the room to give them privacy to interact with QT as they wished. Each interaction lasted about 17 minutes on average ($\pm$ 268 seconds). After completing the interaction, participants again reported their mood using the IMS-12 [52] (M = 5.35, $\pm$.89, α = .94) and described their emotions and feelings in one word using a text box (1WEpost). Following each interaction, participants completed the Regulatory Effectiveness of Social Support Questionnaire (RSS) [53] to assess the extent to which the interaction impacted their understanding of their emotions (3 items; M = 4.67, $\pm$1.37, α = .91) and feelings of control over their emotions (3 items; M = 4.33, $\pm$1.27, α = .93). In each session participants also reported their feelings of hope after interacting with QT [54] (7 items, M = 3.99, $\pm$.65, α = .83).

In the final session, participants reported their ER tendencies using the Short-CERQ [51] after completing the interaction. Upon finishing each session, participants scheduled their next session, were thanked for their participation and provided with contact information of the researchers and of support services, in case needed. Furthermore, after the final session, participants were debriefed about their participation. At the end of the final session, 13 participants volunteered to take part in a semi-structured interview aimed at capturing their overall experiences with the robot-led intervention. Each interview lasted approximately 20–25 minutes. Participants were asked to describe how it felt to talk to QT in general and after each session, to share their most memorable positive and negative moments from the interactions, and to reflect on whether they thought about these experiences afterwards. Additional

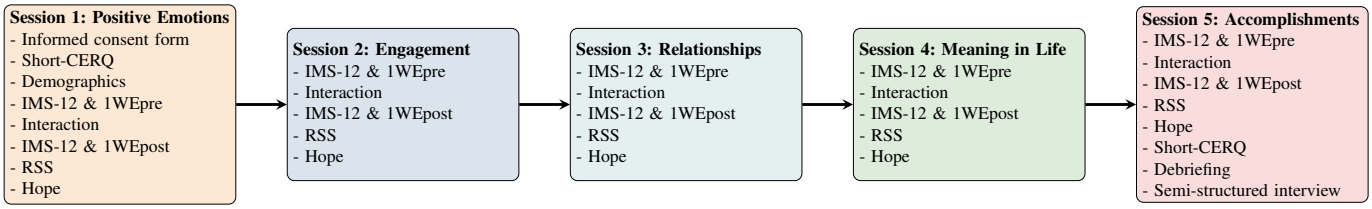


Fig. 4: Flow of the multi-session study according to the PERMA model and the questionnaires reported in each session.

questions probed whether anything QT said stood out to them, how they perceived QT's emotional tone, and whether they would use such a service if it were available on campus. Participants were also asked to consider who might benefit most from talking to QT, under what circumstances they would choose to speak to QT versus a human, and how the experience might change if QT were disembodied or accessed via a screen or smart speaker. The full list of interview questions and the dynamic structure of the interview can be found in Supplementary Material 3. See Figure 4 for the study's flow.

The interactions were recorded (audio and video), and interaction logs were collected to extract measures (see Section IV-G) of speech duration (M = 43.01, ±27.38), compound sentiment (M = .17, ±.19), adjective count (M = 5.42, ±4.84), facial valence (M = -.01, ±.83), and arousal (M = .26, ±.29).

G. Data Analysis

Linear mixed-effects models (LME) were employed using lme4 for R [55] to evaluate repeated measures across the five sessions, accounting for both fixed effects (the session number, and pre/post measures) and random effects (accounting for participant variance). These models were selected for their ability to manage repeated-measures data and ensure robustness in capturing individual differences [56]. Additionally, they were well-suited for data from two cohorts, as modelling participants as random effects inherently accounts for individual variability within and across cohorts, ensuring that cohort-level differences do not confound the overall analysis [57]. Significance was calculated using lmerTest [58] applying Satterthwaite's method [59]. Generalized Additive Mixed Models (GAMMs) were employed to evaluate nonlinear relationships among variables demonstrating nonlinear trends. To capture these trends across the interaction sequence, and to reflect the intervention's unique structure, we modelled the sequence effect using a cubic B-spline, allowing changes to be estimated flexibly at different points in the sequence. This approach enables detection of fluctuations in participants' behaviour that may not follow a strictly increasing or decreasing pattern [60], [61], while also allowing us to test whether any such fluctuations align with predictions related to the reappraisal task. To evaluate how participants' feelings changed due to the intervention, sentiment was extracted from participants' responses to 1WEpre and 1WEpost (see Section IV-F) using TextBlob [62], a tool that calculates sentiment polarity ranging from -1 (extremely negative) to +1 (extremely positive).

The video and audio data were analysed to extract affective meaning. Speech data were processed using Parselmouth [63], a python-based off-the-shelf tool for PRAAT analysis [64] to identify speech duration in seconds. The interaction logs were analysed for verbal expression measures, including sentiment and adjective count. Sentiment was extracted from participants' disclosures using TextBlob [62]. To analyse the distribution of adjectives from participants' disclosures we applied Part-of-Speech (POS) tagging using the Natural Language Toolkit (NLTK; [65]). All text entries were processed using NLTK's word tokenization method. POS tagging was performed on each tokenized sentence to identify adjectives, defined as words classified as JJ (adjective, e.g., happy), JJR (comparative adjective, e.g., happier), and JJS (superlative adjective, e.g., happiest) following Penn Treebank POS tags (see [66]). The count of adjectives per text entry was computed accordingly. For evaluating participants' facial expressions during the intervention, the interaction videos were processed using the FaceChannel dimensional model [67], an off-the-shelf package that predicts valence (how positive or negative the facial expression is) and arousal (the intensity of the facial expression) values [68], ranging from -1 to 1 (see [67]). All behavioural and affective measures were analysed as repeated observations aligned to the interaction timeline. Speech duration, sentiment polarity, and adjective count were computed per participant disclosure turn (N = 619), whereas facial valence and arousal were retained as time-stamped samples across the video (N = 8436). Accordingly, inferential analyses did not collapse interaction segments to a single value; instead, we modelled change as a function of session number and disclosure order.

A thematic analysis [69] was conducted to extract recurring themes from participants' answers to the qualitative interviews. Two trained human evaluators analysed participants' answers, identifying key themes using a systematic, iterative coding process. Initially, they familiarised themselves with the data, then generated preliminary codes that captured both the manifest and latent content of the responses. These codes were subsequently clustered into broader themes through an inductive approach, ensuring that the emerging categories accurately reflected the nuances in the data [69]. The analysis focused on identifying patterns in reflection and introspection, self-regulation, and the perceived affective value of interacting with the robot. Key themes emerged around the participants' sense of emotional support, empowerment, and cognitive reappraisal facilitated by the robot. These qualitative insights were used to complement the understanding of the quantitative results, providing a more holistic view of the intervention's impact.

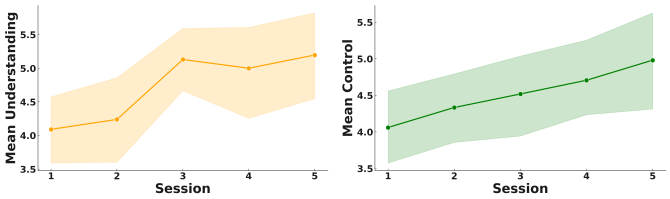


Fig. 5: From left to right: (1) mean score of QT's support in understanding by session. (2) mean score of QT's support in control by session.

V. Results

A. Improved Self-Regulatory Mechanisms

The intervention had a significant positive effect on participants' self-regulatory mechanisms, as indicated by improvements in understanding of their emotional situations and sense of control over the five sessions. As demonstrated in Figure 5, the results stress that despite the variance between the participants ($\pm$1), participants' understanding of their emotional situations increased significantly over time, β = .30, SE = .06, p < .001 (see Table I). Participants' sense of control over their emotions also showed a significant increase, β = .24, SE = .06, p < .001 (see Table I and Figure 5), despite the variance across participants ($\pm$.90).

TABLE I: Mixed Effects Results of Understanding & Control

	Understanding the Situation		Feeling in Control	
Predictors	**Estimates**	**95%CI**	**Estimates**	**95%CI**
Intercept	3.78***	3.19–4.36	3.79***	3.24–4.34
Session	0.30***	0.17–0.42	0.24***	0.11–0.36
Random Effects				
σ^2	0.73		0.68	
τ_{00}	1.00		0.80	
ICC	0.58		0.54	
N	21		21	
Observations	94		94	
Marginal R^2 / Conditional R^2	0.093 / 0.617		0.071 / 0.573	

* p<0.05 ** p<0.01 *** p<0.001

The qualitative feedback from the interviews reveals how QT facilitated participants' understanding of their emotions and empowered them to feel more in control of their emotional challenges. The ability to confront and understand emotional challenges was a recurring theme. P03 remarked, "*When it* [QT] *asked me these sorts of questions, I think I should no longer avoid it, and it's the time to act*" acknowledging that QT prompted them to address long-avoided emotional issues. This was echoed by P09, who stated, "*QT would pick on one of the things that I said that stood out more... and then they would give a question asking me to elaborate... which kind of forced me to think more deeply and closely about that subject that I wouldn't normally do*" reflecting how QT helped them confront and take control of their stressors in a more thoughtful way. Many participants felt that QT's responses encouraged them to reflect on aspects of their emotional lives they typically avoided. For example, P12 shared, "*QT makes you really reflect on stuff that you don't usually engage in those conversations in everyday*" highlighting QT's role in promoting introspection. Similarly, P13 noted, "*they touch on some subjects that I know I normally have a hard time with, but it* [QT] *didn't bother me that much. It* [QT] *was asking questions, and I felt everything was really delicate and within reason – it* [QT] *didn't push too much*", reflecting how QT balanced delicate emotional topics with thoughtful engagement, allowing participants to address difficult emotions without feeling overwhelmed. P03 remarked, "*Talking to it is like I am getting a secondhand option, a different perspective that I should also consider, and it is really hard to see*", showing how QT offered a new perspectives.

Participants also highlighted how QT's supportive comments fostered a sense of control over their emotional states. As P10 noted, "*QT helps organize my thoughts and speak about it in a more organized manner*". QT's ability to help participants confront issues they typically avoided was also evident in P09's experience: "*I think, in my opinion, like it's really nice in the moment, and then maybe might calm you down. But ultimately, the academic stress is still there, the social stress is still there. You haven't really acknowledged or confronted it, whereas with QT you get the opportunity to confront it*". Moreover, QT served as a unique emotional resource compared to other forms of emotional support. As P06 noted, "*I think therapy dogs act more as a distraction, whereas with QT, if you want it to be a distraction, it can be a distraction, but also, if you want it could be a space to discuss the actual problem and try to work through the actual problem. QT is a resource for you*". This reflects how QT provided participants with both a supportive space for emotional regulation and a tool to actively address their challenges, rather than simply offering comfort or distraction.

B. Cognitive Changes in ER Tendencies

The intervention had a significant positive impact on participants' constructive ER strategies (see Table II). The results stress that despite the variance between the participants ($\pm$.37), participants' use of positive reappraisal significantly increased following the intervention, β= .14, SE = .06, p = .017. A significant increase was also observed in acceptance, β = .13, SE = .06, p = .025, despite the variance between the participants ($\pm$.73). Participants also reported a significant improvement in positive refocusing, β = .12, SE = .05, p = .017, regardless of the variance between the participants ($\pm$.68). Also, despite the variance between the participants ($\pm$.59), a significant increase was found in putting into perspective, β = .15, SE = .05, p = .005.

The qualitative results reflect the effectiveness of QT in promoting cognitive reappraisal. Participants frequently mentioned a shift in how they perceived and responded to challenging situations. For instance, P04 noted, "*Stressful events felt way more significant to me... but now, I place more emphasis on the positive things*", demonstrating a reappraisal of negative events by placing greater value on positive experiences. Similarly, P08 highlights this reappraisal process: "*Normally in life we focus on just the negative – something small that happens every day and we put all our attention there. We think that we're worthless the way we have such short amounts. It's nice to remember that whatever you have done are your accomplishments, you know you are not worthless*", suggesting that participants learned to view their actions from

TABLE II: Mixed Effects Results for Cognitive Changes in Emotion Regulation

	Acceptance		Positive Reappraisal		Putting-Into-Perspective		Positive Refocusing	
Predictors	**Estimates**	**95%CI**	**Estimates**	**95%CI**	**Estimates**	**95%CI**	**Estimates**	**95%CI**
Intercept	3.47***	2.99–3.95	3.89***	3.48–4.29	3.38***	2.97–3.78	2.78***	2.34–3.21
Session	0.13*	0.02–0.23	0.14*	0.03–0.26	0.15**	0.05–0.25	0.12*	0.03–0.22
Random Effects								
σ^2	0.43		0.50		0.33		0.33	
τ_{00}	0.53		0.13		0.35		0.47	
ICC	0.55		0.21		0.51		0.58	
N	21		21		21		21	
Observations	42		42		42		42	
Marginal R^2 / Conditional R^2	0.061 / 0.578		0.111 / 0.300		0.116 / 0.566		0.070 / 0.614	

* p<0.05 ** p<0.01 *** p<0.001

a more balanced perspective, reducing the emotional impact of everyday stressors and enhancing their focus on personal achievements. Many participants described how QT helped them reframe negative emotions and gain insight into their situations. For instance, P13 shared, "*It was nice to see a positive outlook on the fact that I'm occupying myself. I thought about it as a negative thing because I was lonely and bored, and the robot said it was a good thing. It was nice to hear it*", Similarly, P07 explained, "*It helped me get some perspective on the situation. It helped me feel a bit encouraged that maybe I could change things and do things in a different way in the future*" showing how QT enabled them to see potential solutions to their emotional difficulties.

Participants also described how QT facilitated a sense of acceptance and self-compassion, which further supports the use of reappraisal. P02 expressed, "*It really helped me be rather accepting of myself... the world doesn't end because I didn't do that one thing that day*", indicating that they had learned to reframe moments of perceived failure as part of a broader, more forgiving perspective on their efforts and accomplishments. P03 shared, "*Talking to QT made me feel confident about different aspects of my past*", reflecting a reappraisal of previously self-critical judgements. Similarly, P06 emphasised that QT guided participants towards "*discovering more things about yourself*", P06 added: "*It's not necessarily QT Telling you and giving you a new perspective, but it's under QT's guidance*". Even when QT was not directly providing new insights, merely speaking to QT and answering to QT's questions supported the practice of reappraisal. This suggests that QT fostered an environment for participants to internally reframe their emotional narratives. Interestingly, the self-reflection facilitated by QT was often described as occurring unconsciously, highlighting the subtle yet impactful nature of the intervention. As P09 noted, "*The self-reflection that I experienced was also kind of subconscious, it wasn't intentional. It just happened while I was interacting with QT*".

The intervention showed no significant effects on maladaptive ER strategies. Participants' use of rumination did not significantly change, β = -.03, $SE = .04$, $p = .362$. Similarly, no significant change was found in self-blame, β = .01, $SE = .05$, $p = .801$. The intervention also had no significant effect on catastrophizing, β = .01, $SE = .04$, $p = .711$, or blaming others, β = -.03, $SE = .05$, $p = .550$. Moreover, in Session 1, participants reported low use of maladaptive strategies: self-blame ($M = 3.24$, $SD = 0.72$), other-blame ($M = 2.49$, $SD = 0.72$), catastrophizing ($M = 2.08$, $SD = 0.82$), and rumination ($M = 3.41$, $SD = 0.73$), demonstrating that such tendencies were already limited at the outset of the intervention.

C. The effects of the intervention on Verbal Expression

TABLE III: Mixed Effects Results for Verbal Expression

	Speech Duration		Sentiment Polarity		Adjective Use	
Predictors	**Estimates**	**95%CI**	**Estimates**	**95%CI**	**Estimates**	**95%CI**
Intercept	29.24***	20.36–38.12	0.23***	0.19–0.28	3.57***	2.11–5.04
Session	3.30***	2.02–4.57	-0.01	-0.01–0.01	0.48***	0.24–0.73
Interaction Order	0.93*	0.07–1.79	-0.01***	-0.02—0.01	0.10	-0.06–0.27
Random Effects and Model Statistics						
σ^2	474.30		0.035		17.48	
τ_{00}	281.33		0.01		6.19	
ICC	0.37		0.04		0.26	
N	21		21		21	
Observations	619		619		619	
Marginal R^2 / Conditional R^2	0.257 / 0.534		0.093 / 0.617		0.132 / 0.364	

* p<0.05 ** p<0.01 *** p<0.001

The progression of the intervention sessions, as well as the order of disclosures within each interaction, had a significant positive effect on the duration of participants' speech disclosures. Despite individual variability between participants ($\pm$16.77), the duration of participants' speech disclosures showed a significant increase over time across sessions, $\beta = 3.30$, $SE = 0.65$, $p < .001$ (see Table III and Figure 6). Similarly, as demonstrated in Figure 6, the duration of participants' speech disclosures significantly increased within each disclosure as the interaction progressed, $\beta = 0.93$, $SE = 0.44$, $p = .034$, despite variance across participants ($\pm$16.78; see Table III). However, when observing the trend in Figure 6, we identified a wave-like pattern in interaction duration that corresponds to the structure of the intervention (see Figure 3). When modelling the effect of disclosure order within interactions using a GAMM, a nonlinear relationship between the order of disclosures and speech duration emerged. The smoothed effect of disclosure order revealed significant increases in interaction duration at multiple points during interactions. Specifically, duration was significantly higher at the second, fourth, and sixth splines, $\beta = 47.11$, $SE = 17.75$, $p = .008$; $\beta = 62.19$, $SE = 17.82$, $p < .001$, and $\beta = 1.82$, $SE = 4.07$, $p = .655$, respectively. In contrast, duration significantly decreased at the first, third, and fifth splines, $\beta = -23.16$, $SE = 12.99$, $p = .075$; $\beta = -50.28$, $SE = 22.72$, $p = .027$; and $\beta = -22.26$, $SE = 12.99$, $p = .087$, respectively.

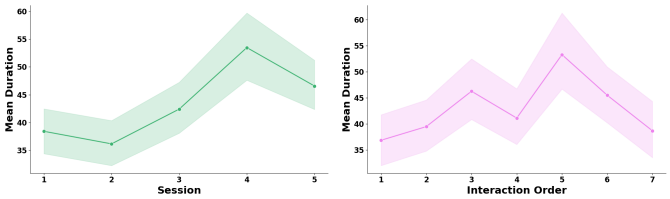


Fig. 6: From left to right: (1) mean speech duration by session. (2) mean speech duration by the disclosure item.

We also found a significant negative effect of the order of disclosures within each interaction on sentiment polarity of participants' disclosures' content. Despite individual variation (±0.01), sentiment scores exhibited a negative significant effect over the order of participants' disclosures within each interaction, β = -0.01, SE = 0.01, p < .001. Conversely, session number did not significantly effect the disclosures' sentiment, β = -0.01, SE = 0.01, p = .575, implying that sentiment changes were more closely tied to the sequential order within interactions rather than to progression throughout the duration of the intervention (see Table III).

Finally, the number of adjectives used by participants significantly increased across sessions, while the order of disclosures within each interaction did not show a significant effect. Despite individual variability between participants (±6.19), the number of adjectives used showed a significant increase over time across sessions, $\beta = 0.48$, $SE = 0.13$, $p < .001$ (see Table III and Figure 7). The order of disclosures within each interaction did not significantly effect the number of adjectives used in linear terms, $\beta = 0.10$, $SE = 0.08$, $p = .222$.

However, when observing the trend in Figure 7, we identified a trend in adjective use that corresponds to the structure of the intervention (see Figure 3). When modelling the effect of disclosure order within interactions using a GAMM, a non-linear relationship between the disclosures order within each interaction and adjective use emerged. The smoothed effect of disclosure order revealed significant increases in adjective use at multiple points during interactions. Specifically, adjective use was significantly higher at the second, fourth, and sixth splines, $\beta = 9.50$, $SE = 1.67$, $p < .001$; $\beta = 9.51$, $SE = 1.68$, $p < .001$, and $\beta = 4.50$, $SE = 0.54$, $p < .001$, respectively. In contrast, adjective use did not significantly change at the first, third and fifth splines, $\beta = -0.015$, $SE = 1.91$, $\beta = 2.87$, $SE = 1.61$, $p = .074$, $p = .994$ and $\beta = 2.13$, $SE = 1.93$, $p = .270$, respectively.

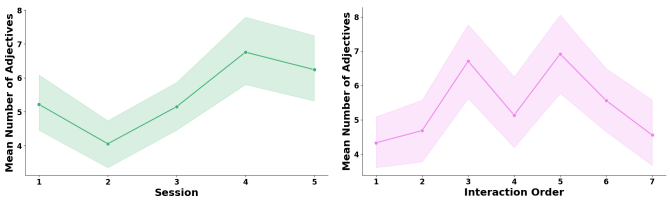


Fig. 7: From left to right: (1) mean number of adjectives by session. (2) mean number of adjectives by the disclosure item.

The observed wave-like fluctuations in both speech duration and adjective use, which peaked at key reappraisal moments, suggest that participants' emotional expressiveness increased overall while also systematically aligning with the intervention's structure. This was particularly evident during reappraisal-focused disclosures, potentially indicating that expressive intensity may be modulated by the cognitive demands of reappraisal, with heightened expression potentially marking moments of emotional engagement and reflective effort.

D. The effects of intervention on facial expression

TABLE IV: Mixed Effects Results of Arousal and Valence

Predictors	**Arousal**		**Valence**	
	Estimates	**95%CI**	**Estimates**	**95%CI**
Intercept	0.15***	0.08 – 0.23	0.34***	0.13 – 0.48
Session Number	0.03***	0.03 – 0.03	-0.02*	-0.03 – -0.01
Interaction Order	0.01***	0.00 – 0.01	-0.05***	-0.06 – -0.05
Random Effects				
σ^2	0.06		0.52	
τ_{00} (Participant)	0.03		0.15	
ICC	0.34		0.22	
N (Participants)	21		21	
Observations	8436		8436	
Marginal R^2 / Conditional R^2	0.10 / 0.42		0.162 / 0.475	

* p<0.05, ** p<0.01, *** p<0.001

The progression of the intervention sessions, as well as the order of disclosures within each interaction, had a significant positive effect on participants' facial arousal levels. Despite individual variability between participants (±0.03), arousal showed a significant increase over time across sessions, $\beta = 0.030$, $SE = 0.002$, $p < .001$ (see Table IV and Figure 8). As demonstrated in Figure 8, arousal significantly increased within each interaction as the interaction progressed, $\beta = 0.006$, $SE = 0.001$, $p < .001$, despite variance across participants (±0.03; see Table IV).

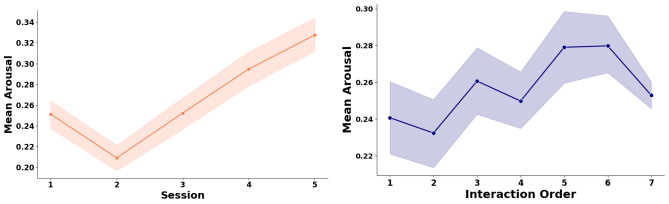


Fig. 8: From left to right: (1) mean score of arousal by session. (2) mean score of arousal by the disclosure item.

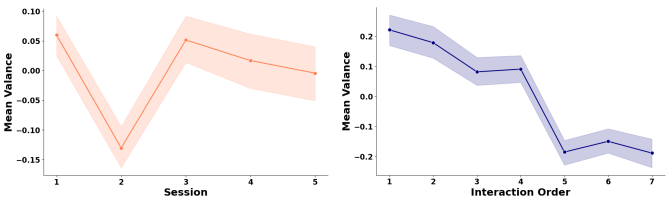


Fig. 9: From left to right: (1) mean score of valance by session. (2) mean score of valance by the disclosure item.

The progression of the intervention sessions and the order of disclosures within each interaction ad a significant negative effect on participants' facial valence levels, indicating

that when participants were engaged in negative disclosure and reappraisal, their valence decreased. Despite individual variability across participants (±0.01), valence declined within each interaction as the interaction progressed, $\beta = -0.05$, $SE = 0.01$, $p < .001$ (see Table IV and Figure 9). Session progression had a significant negative effect on valence, $\beta = -0.02$, $SE = 0.01$, $p = .012$, despite variance across participants (±0.01; see Table IV and Figure 9).

E. Influence on Well-being

As demonstrated in Figure 10, the results stress that despite the variance between the participants (±.62), the intervention had a significant positive effect on participants' mood change following each session. Results revealed a significant improvement in mood after each session, with a fixed effect estimate of β = .59, $SE = .10$, $p < .001$. In contrast, there was no significant effect on mood change over time, β = .02, $SE = .04$, $p = .564$ (see Table V).

Despite the variance between the participants (±.78), the intervention had a significant positive effect on improvement in sentiment after each session, with a fixed effect estimate of $\beta = .16$, $SE = .04$, $p < .001$ (see Table V). There was no significant effect of session number on sentiment change over time, $\beta = -.02$, $SE = .02$, $p = .313$ (see Table V). Moreover, the results stress that despite the variance across participants (±.53), feelings of hope grew gradually over time, with a significant fixed effect by session, β = .06, $SE = .03$, $p = .048$ (see Table V). See the sentiment distribution before and after the interaction in Figure 11.

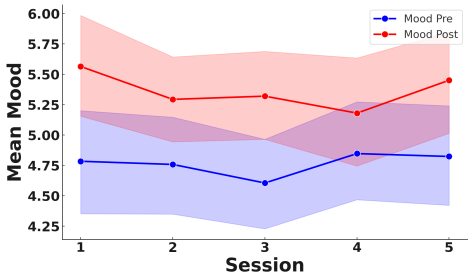


Fig. 10: Mean mood scores before the interaction (blue, lower bar in each session pair) and after the interaction (red, upper bar) across the five repeated sessions. Error bars show 95%CIs.



Fig. 11: Word clouds illustrating the sentiment distribution before (left) and after (right) the interaction.

The qualitative feedback from the interviews underscores the emotional benefits of interacting with QT. P12 expressed how the opportunity to talk about emotions provided a valuable outlet, saying, "*It was nice to take time out of your day to speak to someone about like how you're feeling, which I don't do*". This was echoed by P06: "*QT will usually respond to my response with an additional question or maybe a comment on feeling happy for me, proud of me, or changing my perspective on saying negative or something like that, I found those comments really meaningful*". P01 reflected on how engaging with QT helped them relax, stating, "*I think it was probably in the second session that I warmed up to it. It was quite relaxing*". Similarly, P05 expressed "*I feel better after that than I did before, which surprised me, even with drawbacks that they* [QT] *identified. I guess the idea is that there's an anonymity and a lack of judgment from it, which is good and helpful*". P13 also highlighted the positive emotional effect of the interaction, saying, "*It was really fun, just gaining new perspectives, and it filled me with optimism*". P10 highlighted the importance of such emotional outlets, stating, "*We should have these outlets for people within halls when probably they are feeling the most stressed and wanting to speak to someone*". P09 noted a surprising benefit, saying, "*I never realized that I would feel a lot better after talking about my experiences, whether it be positive or negative. Just saying my experience out loud was really helpful in ways that I did not expect*". This suggests that the simple act of affect labeling (see [28]) with QT provided emotional relief, even for those who did not initially anticipate it. P11 also described how QT's interactions helped them reframe their thoughts and feel more relaxed: "*I think it reframed it in like a sort of positive way to make you think about it again. It made me feel more relaxed*".

TABLE V: Mixed Effects Results of Mood, Sentiment, and Hope

	Mood		Sentiment		Hope	
Predictors	**Estimates**	**95%CI**	**Estimates**	**95%CI**	**Estimates**	**95%CI**
Intercept	4.78***	4.42–5.13	0.27***	0.15–0.39	3.85***	3.56–4.14
Mood Change (pre/post)	0.59***	0.40–0.78	0.16***	0.08–0.24	–	–
Session	0.02	-0.05–0.09	-0.02	-0.04–0.01	0.06*	0.00–0.11
Random Effects						
σ^2	0.46		0.08		0.14	
τ_{00}	0.38		0.02		0.28	
ICC	0.45		0.24		0.67	
N	21		21		21	
Observations	188		188		94	
Marginal R^2 / Conditional R^2	0.095 / 0.503		0.037 / 0.562		0.016 / 0.671	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

F. The role of robotic embodiment

Participants' reflections on QT's embodiment revealed that its physical presence meaningfully shaped the emotional and interpersonal dynamics of the intervention. Many participants described how QT's humanoid form enhanced their engagement and made the interaction feel more like a genuine conversation. P11 explained, *"Having the face and having it sort of like looking around… made me feel more like I'm actually having a conversation"*, while P07 noted, *"Even the way that the face was laid out, like having sort of a gentle smile, was reassuring"*. Participants emphasized how the robot's gaze, facial features, and small gestures such as waving contributed to a sense of co-presence and emotional safety. For example, P01 shared, *"The little wave literally makes me smile every time"*, and P09 added, *"It felt like it was our space, because we're both physically here"*. This sense

of shared presence was often tied to the physical setup of the session, as described by P13: *"I think what I liked about this was that I felt like I was in an enclosed room, where it's just me and Qt, and I can talk about whatever I want"*. Similarly, P05 emphasized: *"It just feels more like... this is the Qt room... this is what this is for... and it's, you know, it's quiet and you can focus on it"*, highlighting how the dedicated environment reinforced the sense of intention and immersion in the interaction. This sense of intentionality was further reinforced by P06, who reflected, *"If it was just there on my phone... I don't know if [I'd remember]... maybe if there was like a dedicated time..."*, and by P02, who explained, *"I'd feel more open and feel more immersed in the experience, talking to a physical robot in like a designated room... versus just kind of pulling out your phone or your laptop"*, noting the feeling that screens are less suitable for ER.

Most expressed a clear preference for QT's embodied form rather than using a screen-based or voice-only interface. P04 stated, *"If it was just like an Alexa... I don't think I would feel as present"*, and P06 remarked, *"I think I would have still preferred QT... because there was like a physical thing that resembled a human, that I could direct all of my messages to"*. Even when acknowledging QT's limited expressiveness, participants described its physical presence as emotionally impactful and conducive to introspection. P08 explained, *"QT helps organise my thoughts. It's like I'm not just talking to myself...I'm talking to QT, and QT's listening. Even though I know it's a robot, it feels like it's paying attention. The little movements, the way it looks at you, it makes a difference. It's under QT's guidance, not just mine"*, reflecting how embodiment supported a relational framing of the interaction. P12 similarly shared, *"I've tried journaling before, but I just end up looping in my own head. With QT, having something physically there, something that looks at you, reacts, and feels present, made it feel more real. Saying things out loud to QT, seeing it nod or smile. It wasn't just me alone with my thoughts, it was like the thoughts had somewhere to go"*. P03 noted this distinction: *"When I talk to a chatbot on my phone, it just feels like I'm typing into a void. With QT, even if it didn't always respond perfectly, it felt like something, or someone, was actually there with me. That made it easier to open up"*.

VI. Discussion

A. Impact on Emotion Regulation

The significant increases in participants' understanding of their emotional situations and their sense of control over the five sessions suggest that the intervention strengthened self-regulatory mechanisms **(RQ1)**. These improvements are crucial for effective ER and have been linked to better psychological outcomes [70]. The enhancement of constructive cognitive ER strategies indicates that participants were also developing long-term skills to manage their emotions more effectively **(RQ2)**. Qualitative feedback further supports these findings, with participants reporting that the robot facilitated deeper introspection and offered a supportive space for discussing emotions. Participants highlighted the robot's role in helping them confront emotional challenges, providing new perspectives and promoting self-reflection. The robot's non-judgemental and consistent presence may have contributed to these outcomes, aligning with previous research suggesting that robots support emotional expression [15].

The absence of significant changes in maladaptive ER strategies suggests that while participants adopted more constructive strategies, they did not increase their reliance on maladaptive ones. This outcome is not unexpected given the scope of the intervention, which was not designed to explicitly target or deconstruct maladaptive tendencies. Reducing maladaptive ER tendencies requires more targeted and intensive interventions, such as those employed in clinical or therapeutic contexts [71]. Accordingly, we can confirm that the intervention does not inadvertently promote negative coping mechanisms. Despite the cognitive effort required to adopt constructive strategies, and the intuitive ease of falling back on maladaptive ones [11], [23], participants improved their constructive ER without exacerbating maladaptive tendencies. While cognitive reappraisal is a beneficial skill, its implementation, particularly when prompted by an external entity (or in this case, a system), can sometimes backfire or inadvertently trigger maladaptive patterns [72]–[74]. This balance highlights the intervention's potential in fostering healthy reappraisal without unintended side effects, highlighting the safety and emotional suitability of the intervention.

B. Effects on Expression

Throughout the intervention, participants expressed themselves more richly and openly, using longer speech durations and more descriptive emotional adjectives, while also being more expressive non-verbally (i.e., through facial expressions) **(RQ3)**. This key finding reinforces previous HRI research, showing that people gradually open up to robots when disclosing about themselves over time [15], [29], [30]. Our findings extend previous results by showing that, beyond disclosing more over time, people's disclosures to robots are also more affective in nature and correspond to their ER practices. This aligns with affect labelling theory, suggesting that articulating emotions helps regulate them [28].

Throughout the duration of their participation, participants enriched their disclosures with more descriptive language, incorporating a greater number of adjectives, potentially indicating deeper cognitive processing of their emotions and experiences. These findings may suggest that cognitive reappraisal with the robot appears to operate on two levels, changing interpretations while fostering cathartic expression, supporting the idea that verbalizing and reinterpreting emotions enhance regulation. Moreover, increased self-disclosure during reappraisal extends prior research on self-disclosure to robots [15], [29], [30], further demonstrating its role in therapeutic improvement [75], [76]. Importantly, our results indicate that encouraging emotional expression during reappraisal does not overwhelm individuals but rather facilitates the process and improves outcomes. Future research should further validate this finding by evaluating whether the presence of the robot facilitating the intervention encouraged participants to engage in expression rather than suppression, or whether this effect

was merely due to the task itself. Previous evidence from ER training [77] and interpersonal ER research [78]–[80] indicates that incorporating a social element can significantly enhance cognitive reappraisal by engaging interpersonal processes that foster reflection and reinterpretation of emotional experiences. Accordingly, based on our quantitative and qualitative findings, we propose that the robot's social presence and interactivity may have positively impacted participants' ER performance in this experiment.

Interestingly, participants' expressed sentiment, verbal and non-verbal, became gradually more negative within each session, even though their overall mood improved by the end. As conversations progressed, deeper reflection during the **NCQ** and **CR** disclosure items (see Section IV-F) appeared to prompt more negatively valenced speech and facial expressions, accompanied by heightened emotional arousal (i.e., greater facial arousal, denser adjective use, and longer disclosures). This trend suggests that, rather than suppressing difficult emotions [81], participants engaged in reappraisal through genuine expression. This interpretation is supported by qualitative feedback, where participants noted that the robot helped them explore suppressed emotions and reconsider their perspectives. The observed pattern, initial emotional expression followed by cognitive restructuring, bridges a gap in ER theory, suggesting that effective reappraisal may involve allowing negative expressions to peak before relief is achieved [82], [83]. These findings highlight a dynamic trajectory in robot-assisted ER, where encouraging expression, even of negative emotions, plays a crucial role in the regulation process. Our results support the premise that self-guided interventions [84], [85], including technology-assisted interventions [86] such as social robots [18], [19], may help individuals navigate this dynamic mechanism while minimizing negative social consequences [15]. Although facial valence became more negative as the interaction progressed, this pattern is expected given that the session structure culminates in a negative-connotation disclosure followed by a cognitive reappraisal [87]. The momentary decrease in facial valence during negative disclosure/reappraisal likely reflects engagement with challenging content (and the cognitive effort of reframing it), whereas the mood measure captures participants' affective state after completing the reappraisal process.

From an affective computing perspective, our analysis of speech sentiment, facial expressions, and linguistic markers of self-reflection provides a framework for assessing users' emotional engagement in real-world HRI. While our study applied this analysis post-hoc, it highlights how multi-modal affect data can be leveraged to evaluate the effectiveness of interventions. Future affect-aware systems could build on this by exploring how changes in verbal and nonverbal cues correspond to shifts in ER over time. These findings add up to earlier work demonstrating how multimodal analysis of speech and sentiment in controlled HRI settings can reveal users' emotional engagement [88].

C. Effects on Well-being

The improvement in mood and increased positive sentiment after each session show that the intervention had a beneficial effect on participants' emotional states **(RQ4)**. While no cumulative effect on mood was observed over time, the consistent positive impact after each session underscores the intervention's effectiveness in providing swift emotional support. For university students, who often face high levels of stress and emotional challenges due to academic pressures, personal development, and social expectations [1], such swift and on-the-spot emotional uplift can be particularly valuable. Enabling students to access readily available supportive agents within their natural environments may help them better manage emotional difficulties as they arise, potentially preventing the escalation of stress into more serious mental health issues. These findings align with previous work showing that individuals experiencing negative emotions were more likely to engage in expressive interactions with a social robot, using the robot as an emotional outlet during distressing times [89].

While no cumulative increase in mood was observed across sessions, this pattern is consistent with the conceptualization of mood as a transient and context-sensitive state [90], and previous results in multi-session HRI studies aimed at eliciting positive mood change [29], [30]. In this study, mood was measured to capture immediate emotional shifts resulting from each interaction, rather than to reflect long-term change. The consistent post-session improvement suggests that the intervention reliably supported in-the-moment emotional uplift-ment. In contrast, cumulative effects were evident in constructs more closely tied to enduring emotional adaptation [91]. This distinction highlights the importance of evaluating both short-term and longer-term outcomes when assessing the impact of emotionally supportive interventions with robots.

D. Individual Differences in Intervention Response

After controlling for substantial between-subject variance, session effects remained positive and significant, confirming genuine within-subject improvements over time despite individual differences. Students who began with lower scores in constructive strategies or with briefer disclosures showed the steepest gains, while those starting near the top exhibited minimal change, an expected ceiling effect. Maladaptive strategies remained low and static, suggesting that the intervention neither triggered harmful coping nor had much room to reduce it further. Despite inter-individual differences in self-regulation mechanisms (i.e., emotional understanding and control), both indices increased session by session, indicating that students progressed relative to their own baselines. Because the random intercepts capture these stable differences, the fixed session effects reflect a shared upward trend across the cohort. Overall, these findings indicate that the intervention delivers robust average benefits while accommodating substantial individual variability. Adapting prompt depth or session frequency to participants' baseline ER capacities may further enhance these benefits, helping high-baseline students move beyond ceiling levels and offering greater support to those starting lower.

E. Perceived Value of Robot Embodiment

The results highlight that QT's embodiment played a meaningful role in shaping participants' engagement with the intervention. While the robot's verbal content was driven by

an LLM, participants consistently attributed emotional significance to QT's physical presence, gestures, and the shared spatial environment. The embodiment fostered a sense of co-presence and social connection and created a structured, intentional setting for reflection, something participants contrasted with more familiarinteractions with disembodied agents and journaling apps. These insights shared by the participants are in line with previous quantitative results in the field showing the socio-affective benefits of robotic embodiment over disembodied agents [88], [92]. The robot's form anchored the experience in a way that felt distinct from disembodied interfaces, suggesting that even minimal embodiment can transform user perceptions of affective interactions with AI-powered artificial agents, underscoring the importance of considering not just *what* is said, but *how* and *where* it is delivered.

VII. Limitations and Future Research

The study demonstrated promising outcomes, though several limitations should be considered. One limitation is the absence of a control group, which limits direct attribution of the effects solely to the intervention. However, in longitudinal HRI studies in real-world settings, control groups can be impractical due to environmental variability, inconsistent participant experiences, and logistical constraints [93], [94]. To mitigate this, a within-subjects design was used, allowing participants to serve as their own controls [95], while LMEs accounted for both fixed and random effects, controlling for confounds over time [56], [96]. This approach provides a robust framework for analysing the intervention's impact in naturalistic settings while sustaining optimal power for explaining results [57]. Future studies could conduct controlled comparisons with disembodied agents to better understand how the robot's physical presence in familiar, in-situ environments, together with its embodied cues, supports emotional interactions, in contrast to more accessible chatbots and screen-based avatars. Moreover, our sample size may be perceived as relatively small; however, this study was a multi-session, mixed-methods investigation in everyday settings. The sample size was determined through an a priori calculation to ensure sufficient power [38] and the data acquired and analysed aligns with previous HRI studies [97]. Accordingly, our conclusions are scoped to within-person effects observed in this student sample and in-situ setting, and broader generalizability should be established through replication across more diverse populations and contexts.

Another potential limitation is that although the intervention took place in familiar environments, it required scheduled sessions rather than fully spontaneous, on-demand use. However, this is consistent with the structure of many interventions, which prioritize safety, consistency, and emotional or cognitive value [98], [99]. Our design aimed for ecological integration without overestimating current robot autonomy or sacrificing experimental control. In addition, robot-based interventions require physical infrastructure, room availability, and scheduling, which can constrain accessibility and reach. This trade-off between the benefits of embodiment (e.g., engagement, rapport) and the limitations of scalability (e.g., infrastructure, scheduling) is well-recognized in HRI literature [16], [100]. To mitigate these limitations, the intervention was embedded within participants' routines using a low-effort booking system that allowed them to schedule sessions at their convenience. While this format limits spontaneity and large-scale deployment, it enables integration into shared institutional settings, reducing pressure on human-led services and expanding access within existing resources. Future work could explore more ad-hoc deployments as robotic systems become more autonomous and capable of providing consistent emotional support in less structured or unsupervised environments.

Additionally, while the intervention promoted constructive ER strategies, it did not significantly reduce maladaptive ones. Future work could tailor interventions to minimise reliance on maladaptive strategies. Finally, given that this intervention primarily focused on prevention and fostering adaptive skills, future research should examine whether such interventions are appropriate for individuals exhibiting clinical symptom severity. Participants with a history of trauma or more severe psychological symptoms [101], may require the support of a professional mental health provider alongside their participation in robot-led interventions [99].

VIII. Conclusions

Our findings highlight the role of social robots in facilitating cognitive change and in fostering richer emotional expression, which is central to effective ER. Notably, beyond the linear effects of increased expression over time, we also identified structured patterns of expressiveness aligned with the cognitive reappraisal process: participants expressed themselves more, and more positively in terms of sentiment and facial valence, within each session, with expression peaking during key reappraisal moments, particularly when the robot prompted them to reinterpret negative experiences using prior positive disclosures. This structured expressiveness underscores how robot-mediated reappraisal can guide users through a dynamic regulatory process, facilitating both emotional expression and cognitive change in a way that mirrors evidence-based therapeutic techniques. A single social robot installed in a school, clinic, or workplace could support many people who share that space, easing emotional challenges and supplementing human support, both now and as demand continues to grow.

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