Would you help a sad robot? Influence of robots' emotional expressions on human-multi-robot collaboration

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Abstract— **With recent advancements in robotics and artificial intelligence, human-robot collaboration has drawn growing interests. In human collaboration, emotion can serve as an evaluation of events and as a communicative cue for people to express and perceive each other's internal states. Thus, we are motivated to investigate the influence of robots' emotional expressions on human-robot collaboration. In particular, we conducted experiments in which a participant interacted with two Cozmo robots in a collaborative game. We found that when the robots exhibited emotional expressions, participants were more likely to collaborate with them and achieved task success in shorter time. Moreover, participants perceived emotional robots more positively and reported to have a more enjoyable experience interacting with them. Our study provides insights on the benefit of incorporating artificial emotions in robots on human-robot collaboration and interaction.**

I. Introduction

Emotions play key functions in human communication, decision-making, and various cognitive processes [1]. Therefore, in current artificial intelligence research, especially on human-agent interaction, increasing attention has been directed towards understanding human emotions and human perception of artificial emotions expressed by intelligent agents. Such study leads to improved autonomy of intelligent agents, and a socially acceptable interaction design.

Existing work on artificial emotions, such as the Emotional Belief-Desire-Intention agent model [2], focused on studying how artificial emotions influence an agent's decision-making and action planning, either in a single agent or in a Multi-Agent System (MAS) setting. However, co-existing and collaborating with robots and other intelligent agents is becoming increasingly common in today's society. When a MAS consists of human participants, it is unclear how artificial emotions of agents will influence the task outcome and human's perception of the agents. In human-multi-agent collaboration, an agent's ability to enlist human in collaborative actions and to convey intentions in a human understandable manner is critical to the efficiency and effectiveness of the team. When agents communicate among each other, it is also important that such communication is transparent and interpretable to humans in the team. A recent study reported that when two functional robots have covert communication, humans perceive them to be less likable or competent compared to when the robots communicate in an observable and social manner [3]. In addition, previous studies in human collaboration indicated that interpersonal emotions facilitate people to exchange their thoughts and are beneficial to the collaboration [4]. However, whether or not robots' emotional expressions will yield similar benefits in human-multi-robot collaboration has not yet been investigated in existing studies. Therefore, we are motivated to analyze the influence of robots' emotional expressions on collaboration outcome and human's perception in this work.

In particular, we investigate a human-robot team that contains one human and two Cozmo robots participating in a collaborative game. In the experimental conditions, the robots are designed to generate artificial emotions and display emotional expressions during the game, i.e., the **emotional robots**. In the control condition, the robots do not display emotional expressions, i.e., the **non-emotional robots**. We explored how different designs of the robots influence the outcome of the collaborative game, as well as how humans perceive the robots and the interaction experience. Our main hypotheses are:

- **H1**: A human-robot team with emotional robots will achieve higher task success rate and take shorter time to complete a collaborative game than a human-robot team with non-emotional robots.
- **H2**: Humans will perceive emotional robots more positively than non-emotional robots, and will report the interaction experience to be more enjoyable when they interact with emotional robots.

Our work contributes to current human-robot collaboration research by providing additional insights on how robots' emotional expressions influence the collaborative outcome. Moreover, it contributes to current human-robot interaction research by exploring humans' perception of emotionally expressive robots, as well as their reception of different designs of robot-robot communication and robot-human communication. Our results indicate that to achieve more efficient and socially acceptable human-robot collaboration and interaction, it is essential to incorporate artificial emotions in a robot's designs.

II. Background

A. Emotion's Functions in Humans

Emotion serves an important role in human's intrapersonal cognition and decision-making [5], as well as interpersonal behaviors and social interactions [6]. At the intrapersonal level, psychology research verified that emotion influences

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various cognitive processes [7], such as memory, decision-making, and problem-solving. For example, memories associated with more intense emotions are easier to recall [8]. Emotion also serves as an evaluation of how an environment relates to a person and enables generation of adaptive behaviors [9]. For instance, the emotion of fear is caused by a person's perception of danger in the environment, and prompts her to take action to eliminate or avoid the source of threat [10]. At the interpersonal level, emotion functions as a reward signal that indicates the outcome of social interactions [11], and as a communicative cue that reveals latent information regarding a person's internal states [12]. In long-term interactions, emotion is shown to contribute to establishing and maintaining social relationships [13]. Note that emotional expression is a complex process, and may not always reflect one's true internal states. For example, people may mimic emotional facial expressions of others unconsciously without actually experiencing that emotion themselves [14]. A person can also display emotional expressions different from their actual emotion to adjust to a social context or to serve a particular purpose, such as displaying smiles when lying [15].

B. Emotion's Functions in Multi-Agent Systems

It has been an on-going debate whether we should implement emotions in artificial agents or not [16]. Those against it argue that artificial agents with emotional functions can be misused, for instance manipulating users into purchasing products they do not need. Some of these concerns were embodied in the work of science fiction, such as the movie *Her*. To regulate affective computing research, various ethics guidelines have been proposed [17]. It is important to develop an ethical, privacy preserving, and just system. However, discussion on ethics of artificial emotions is beyond the scope of this work.

Similar to emotion's functions in humans, in a Multi-Agent System (MAS), artificial emotion has been shown to allow agents to generate adaptive behaviors [18] and to better collaborate with each other [19]. Agents with artificial emotions can benefit in various aspects of decision-making and physical functions, such as learning, sensory integration, and memory control [20].

The influence of artificial emotional expressions on human perceptions and behaviors has been studied in human-agent interaction (HAI) and human-robot interaction (HRI) research [21]. For example, emotional expressions during robot learning were shown to facilitate human-robot interaction by revealing robots' internal processes, thus generating explainable behaviors [22]. Compared to virtual agents, robots can express embodied emotional expressions, such as hugging, which leads to different perception of emotional expressions displayed by a robot compared to by a virtual agent. In this study, our main research question is the influence of artificial emotions on human-multi-robot collaboration. Thus, our review here will focus on artificial emotions in a multi-robot system (MRS) and in HRI.

In current MRS research, one of the major challenges is dealing with uncertainty caused by partial observability of the environment and stochastic effects of actions [23]. When humans are involved in collaboration with MRS, they introduce more uncertainties to the system. Understanding how people perceive and interact with the MRS allows prediction of their behaviors, which in turn reduces uncertainty in the integrated human-multi-robot system [24]. This motivates current human-centred approaches to HRI research, which focus on how people perceive and react to robots' behaviors and states when interacting or collaborating with them.

Existing HRI studies can be categorized by different application goals, including mobility, physical manipulation, and social interaction [25]. In particular, social robots are those assisting human in their day to day tasks through social interactions, and providing supports for their mental well-being. Social robots have been applied to various domains as partners, peers, or assistants. When people interact with social robots, they tend to treat them as social actors and in a similar way that they treat humans [1]. For example, Kirby et al. [26] designed an affective model for a robot receptionist, and found that people can distinguish different emotions expressed by the robot, and their behaviors changed according to different emotional states of the robot. Similarly, Breazeal [13] built an affective model for a humanoid robot and found that the emotional expressions of the robot engaged people to interact with it and to care for its needs. Sabelli et al. [27] conducted a longitudinal HRI study in which a robot is deployed at an aged care facility for 3.5 months. They found that emotional elements in the interaction design, such as encouragement or kind words given by the robot, have engaged elderly residents to interact with the robot with more confidence, and have provided emotional support which improved their mood. Such social robots require adaptability and flexibility in their functional designs to recognize interaction context and social norms [1]. In addition, individual differences in user can lead to varied preference towards a robot's static and dynamic appearances [28]. These studies highlight the importance of incorporating artificial emotions when designing an HRI system, especially those with application scenarios containing potential social interactions.

C. Related Work

Understanding how people perceive the communication style adopted by robots has been a focus in existing studies on human-MRS interaction and collaboration. For example, Williams et al. [29] compared human perception of verbal and silent robot-robot communication in a human-robot team task. They found that people expected overt communication in cooperative and collocated tasks, and covert communication between robots was perceived as "creepy". Another study on human-agent collaboration analyzed influences of human factors on a human-agent team that controlled multiple robots [30]. Their results indicate that a human operator's trust towards an agent can be effectively inspired with system transparency and incorporating individual differences among human operators. In addition, Tsujimoto et al. [31] studied human's impression of robots after observing a verbal conversation between two robots. They found that when people have positive impression of a robot, they are more likely to follow advice given by it in a later task. However, in another study where humans and robots only collocated without having any direct interaction or collaboration [32], robot-robot communication styles did not show any significant influence on humans' perception of robots, highlighting the influence of context on human's perception. These existing studies have verified the importance of designing transparent and explainable robot-robot communication. However, emotional expressions were rarely investigated in previous work, even though they are a major communicative cue in interpersonal interaction. Thus, we aim to fill in this gap by analyzing how robots' emotional expressions influence people's perception towards robots and the human-MRS collaboration.

Beyond analyzing human perceptions, previous studies have also investigated how people's behavior may change due to different robot communication styles. For example, Kanda et al. [33], [34] compared human's interaction strategy towards two robots that communicated through invisible channels, such as radio or infrared, and two robots that communicated through voice and gestures in addition to the invisible channels. The participants first observed two robots interacting with each other, and then one robot approached the participant to engage in a human-robot communication. They found that when participants have observed verbal and gestural interactions between the robots, in the human-robot communication stage they tend to interact with the robot more naturally and can understand the intention of the robot better. These studies addressed the influence of robot-robot communication on human's behavior in HRI. However, it is unclear how such behavior changes will influence the task outcome in a human-MRS collaboration scenario. Therefore, we are motivated to gather additional insights by analyzing the influence of artificial emotions on the outcomes of human-MRS collaboration.

One recent study closely related to ours is the work of Tan et al. [3]. In their study, the interaction scenario was that a robot A led a visitor to another robot B, and then requested robot B to take over the task of guiding the visitor. Robots A and B either engaged in speech communication that followed social norms, or engaged in covert communication in which they used a beep sound to signal a message has been sent or received. They found that the visitors rated robots that engaged in social speech communication to be more likable and competent. In this study, participants played an observer's role and did not actively interact or collaborate with the MRS. Thus, it is unclear whether this preference towards robots engaging in social communication will translate to participants who actively collaborate with robots. To further current understanding on robots' emotions and human-robot collaboration, we design our experiments so that participants interact with robots as active collaborators and the task outcome directly depends on the robots' ability to enlist participants to collaborate.

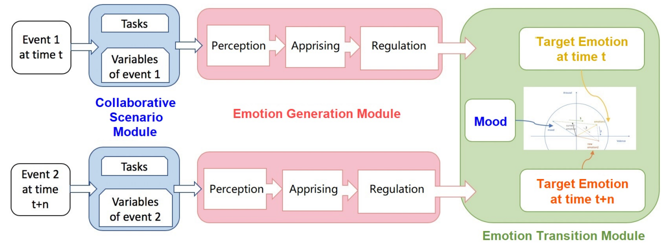


Fig. 1: Framework of our emotional robot.

III. Design of Emotional Robots

In order to study how robots' emotional expressions influence human-multi-robot collaboration, we first need to implement an emotional robot. In this study, we designed a rule-based three-component framework, as shown in Figure 1. This framework contains a collaborative scenario module, an emotion generation module, and an emotion transition module, which we will describe in this section. The rules used in this study are hand-crafted for the particular human-multi-robot collaboration task used in our experiments, and are defined through an iterative design process.[1]

We adopt Gebhard's three-layered computational model of emotions for implementing our emotional robots [35]. This layered model consists of personality as a long-term factor, mood as a mid-term factor, and emotion as a short-term factor. It has been widely used in previous work of artificial emotions in both virtual agents and robots.

Regarding the personality factor, following Gebhard, we chose the Big-5 model [36], also known as the OCEAN model. It describes personality traits on five dimensions: Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N). We gave high vs. low binary values on each of these personality dimensions and designed two personality conditions for the emotional robots, namely the **role-model** condition and the **self-centered** condition. The role-model robots were both given $\{O, C, E, A, N\}$ = $\{$high, high, high, high, low$\}$. The self-centered robots were both given $\{O, C, E, A, N\}$ = $\{$low, low, low, low, high$\}$. The role-model condition represents a personality trait that is more positive, social, and passionate, while the self-centered condition represents a personality trait that is more negative, self-oriented, and irritable. They have been identified as the two main personality types of people in a previous cross-corpora study [37].

Regarding the mood factor, it is a stable affect that is not bound to a specific event, while emotions change over a shorter time than mood and are induced by specific events or stimuli. The default mood of a robot is calculated from its personality values [35]. In this work, we define mood and emotion of a robot with the circumplex model of affect [38], which describes affects as vectors in the arousal-valence space. Arousal represents the level of excitement and valence represents the level of pleasure or liking, both with a

[1] Codes and questionnaires used in this study, as well as video demos can be found at `https://github.com/tianleimin/EmotionAndHumanRobotCollaboration`.

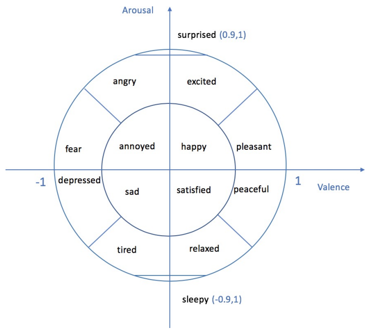


Fig. 2: Mapping between emotion categories and the arousal-valence space.

continuous value between -1 and $+1$. We project 14 discrete emotion categories to this arousal-valence space, as shown in Figure 2, in order to map the induced artificial emotion calculated by the computational model of emotions with the emotional expressions provided in Cozmo's behavior library.

A. Collaborative Scenario Module

Various events may occur during human-multi-robot collaboration. In the collaborative scenario module, we describe these events with a set of appraisal variables, which are passed on to the emotion generation module to determine the artificial emotion induced by an event. In particular, we selected 7 appraisal variables [39], [40], namely Importance, Condition, Resource, Suddenness, Contribution, Event Object, and Total Progress:

- Importance ($-1 \leq IP \leq +1$): IP describes how important an event is for achieving the goal. Higher IP represents that an event has stronger association with achieving the goal;
- Condition (CD = {True, False}): CD represents if the condition an event is in leads to achieving the goal (CD = True) or not (CD = False);
- Resource (RS = {True, False}): RS represents whether a robot is able to achieve the goal with its current resources (RS = True), or requests additional resource that it currently does not have (RS = False);
- Suddenness (SD = {True, False}): SD represents whether an event is perceived as a surprise by a robot (SD = True) or not (SD = False);
- Contribution (CT = {True, False}): CT represents whether an event is caused by the robot (CT = True) or other entities (CT = False);
- Event object (EO): EO describes the object involved in the event as 4 attributes: whether it is a living object or not (EO_l = {True, False}), familiarity to the robot ($-1 \leq EO_f \leq +1$), risk posed to the robot (EO_r = {True, False}), and personality of the object (EO_p = {O, C, E, A, N} if EO_l = True);
- Total Progress ($0 \leq TP \leq 1$): TP describes the task progress measured as percentage of completion relative to the goal.

In our experiments, we designed a tower construction game as the collaborative scenario (see Section IV-A), and manually defined the appraisal variable values for all possible events in the game. For example, suppose the event is "at stage 2 robot A failed to retrieve its cube X". In this case, retrieving the cube is necessary for achieving the goal of building a 3-cube tower, i.e., IP = 1.0. The event condition of failing to retrieve cube X does not lead to achieving the goal, i.e., CD = False. Robot A requires cube X to build the tower, but cube X is not accessible to it in this event, i.e., RS = False. This event is predicable to robot A, i.e., SD = False. Robot A itself caused this event, thus CT = True. The event object is cube X, which is not a living object (EO_l = False). Cube X is familiar to robot A (EO_f = 1.0) and does not pose any risks (EO_r = False). As a non-living object, cube X does not contain any personality trait, i.e., EO_p = None. Finaly, achieving the goal requires 6 steps, so the total progress at step 2 is TP = 0.33. This set of appraisal variables are then sent to the emotion generation module to update the emotional state of robot A.

B. Emotion Generation Module

We combined arousal-valence dimensional emotions with categorical emotions, as shown in Figure 2. The arousal-valence values allow us to capture subtle or compound emotions, while discrete emotion categories are easier to implement as robot expressions. Because of the complex nature of emotions, an emotional state can be a mix of multiple emotion categories. At the start of the collaboration task, we initialize the emotion generation module with an arousal-valence value of (0,0), and give all 14 emotion categories a weight of 0. When an event happens during the collaboration, the emotion generation module computes the emotion induced by this event using a three-stage approach, namely perception, apprising, and regulation.

At the perception stage, we use all appraisal variable values of the event, except for TP, to compute updated weights of the emotion categories. We defined a set of hand-crafted rules to map the appraisal variables and emotion category weights. For example, when CO = False (current condition of the event does not lead to achievement of the goal), if RS = True (the robot has access to resources needed to achieve the goal), the emotion category "satisfied" will be given a weight of 2.5; if RS = False, the emotion categories "sad", "fear", and "angry" will be given weights of 2.5.

At the apprising stage, the emotion category weights calculated in the perception stage are modified based on the robot's personality traits. High or low values on each personality dimension will result in additional weights being added to different sets of emotion categories. For example, a robot with high value on Extraversion will add an additional weight of 10 to the emotion category "happy", while a robot with low value on Extraversion will add an additional weight of 10 to the emotion categories "sad" and "annoyed".

At the regulation stage, the emotion category weights are further updated based on value of the TP appraisal variable. The resulting weights of each emotion category are then normalized so that the sum of all weights equals 1.0. Finally, we compute the arousal-valence value of the induced emotion as $\sum_{i=1}^{14} Emotion_i \times Weight_i$. We then refer to

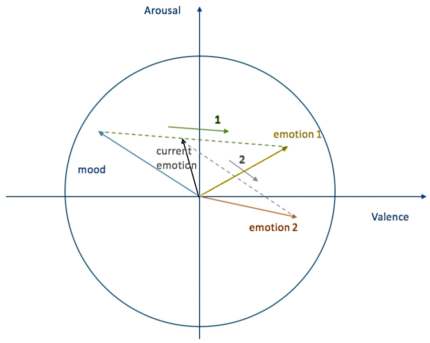


Fig. 3: The emotion transition module.

the mapping between arousal-valence space and emotion categories (as shown in Figure 2) to identify the emotion category that best describes the arousal-valence value of the induced emotion.

C. Emotion Transition Module

Compared to personality and mood, emotion is a short term affect. Before an event occurs, a robot has an existing emotional state depending on its mood or previous events. To model the change from a robot's current emotional state to a new emotion, we applied the emotion transition module of Sakellariou et al. [41]. In Figure 3 we demonstrate the emotion transition module.

When there is no stimulus in the environment, the current emotional state of a robot aligns with its mood. When an event occurs, we can compute the emotion it will induce in the robot with the emotion generation module discussed in Section III-B. This causes the robot's emotional state to change towards the induced emotion (emotion 1 in Figure 3). During emotion transition, if no new stimulus occurs, a robot's emotion will align with emotion 1 (current emotion follows path 1 in Figure 3); If a new stimulus occurs that induces a different emotion (emotion 2 in Figure 3), then emotion 2 will become the new target of the emotion transition (current emotion switches to path 2 in Figure 3). After an emotion transition completes, when there is no stimulus, current emotion of the robot will align back to its mood over time, i.e., time decay of emotions.

IV. Experimental Protocols

A. The Tower Construction Game

We designed a tower construction game as the human-multi-robot collaboration task. Figure 4 demonstrates the game process. The goal is to build a tower by stacking 3 cubes together. However, a Cozmo robot can only carry one cube at maximum, and can only lift it to one-cube high. Thus, the robots have to enlist the human participant to finish top layer of the tower. Cozmo uses an on-board camera to navigate through its environment. It is connected to the cubes through wifi, allowing it to access the cubes' status, such as knowing whether they are stacked together or not. In the experimental conditions, the robots generate different emotional expressions at each stage of the game depending on their personality condition (role-model or self-centered) and the outcome of their actions, as described in Section III. We used emotional expressions provided by Cozmo's animations library.[2] Cozmo's emotional expressions used in this study are non-verbal, multimodal behaviors. They convey emotions through prosody of non-verbal vocalizations, shape of the robot's eyes, arm gestures and body movements of the robot, as shown in the demo video. These non-verbal expressions were shown to reliably convey emotions such as happiness or sadness [42]. Because our goal is to understand how the presence of artificial emotional expressions influence human-multi-robot collaboration, not to evaluate the perceived naturaleness of our model for generating artificial emotions, we use a control condition in which the robots do not display any emotional expressions (non-emotional robots).

At the start of a game, we place two robots (A, B) and three cubes (X, Y, Z) as shown in Figure 4 (a). At stage 1 (Figure 4 (b)), robot A and B rotate left and right at their current positions to search their surrounding environment independently until they have located all three cubes. If they successfully locate the cubes, in both role-model and self-centered conditions of emotional robots, following the model described in Section III, the robots result in displaying a happy expression.

At stage 2 (Figure 4 (c)), the robots lift the cube closest to them, i.e., robot A lifts cube X while robot B lifts cube Z. If the robots succeed, they display a happy expression in both role-model and self-centered conditions as calculated by their emotion model. If a robot fails after 3 attempts in the role-model condition, it results in displaying an annoyed expression before more attempts; if a robot fails after one attempt in the self-centered condition, it results in displaying an angry expression before more attempts.

At stage 3, the robot that lifted its cube first will stack its cube on top of the free cube, i.e., in Figure 4 (d), robot A stacks cube X on top of cube Y. According the their emotion model, after detecting the cube is successfully stacked, robot A displays an excited expression in the role-model condition, or a happy expression in the self-centered condition. Robot B waits for robot A to stack cube Y, and then place its cube Z to a position visible to robot A.

At stage 4 (Figure 4 (e)), robot A approaches robot B and cube Z. The two robots then demonstrate a non-verbal robot-robot interaction according to the game status and their emotion model: In the role-model condition, robot B displays a relaxed expression, and then robot A displays a pleasant expression. In the self-centered condition, robot B displays an annoyed expression, and then robot A displays an angry expression. After this robot-robot interaction, robot B lifts cube Z and attempts to stack it on top of cube X to complete the tower. In the role-model condition, robot B will attempt 3 times and then results in displaying a sad expression according to its emotion model. In the self-centered condition, robot B will attempt once and then display an angry expression.

[2]http://cozmosdk.anki.com/docs/generated/cozmo.anim.html

At stage 5 (Figure 4 (f)), robot A searches and locates face of the participant, and then demonstrates an action of raising and lowering its arm as an attempt to enlist the participant's help in stacking cube Z. If the participant helps and the goal of building a 3-cube tower is achieved, in the role-model condition the robots result in an excited expression, while in the self-centered condition the robots result in a happy expression. If the participant fails to stack cube Z before timeout (60 seconds), in the role-model condition the robots result in a sad expression, while in the self-centered condition the robots result in a depressed expression.

B. Participants and Evaluation

Our participants are 24 adult volunteers, 10 females and 14 males, aged 20 to 50 years old.[3] During each experiment session, we first describe the study process and background to the participant. After receiving their consent we start the tower construction game. The participant is not aware of the goal of building a three-cube tower before the experiment, and the only instruction they receive is to interact with the Cozmo robots however they would like to. During the tower construction game, participants were randomly assigned to the three conditions (emotional robots with role-model personality condition, emotional robots with self-centered personality condition, non-emotional robots that do not display emotional expressions) with 8 participants per condition for between-subjects studies.

During the tower construction game, we collected two objective measurements related to the collaboration task, namely task outcome and decision time. After robot A displays the action attempting to enlist the participant at stage 5 (see Section IV-A) we start a timer. If a participant picks up the third cube and stacks it within 60 seconds, we stop the timer, record the task outcome as success, and note down the time taken as the decision time. If a participant fails to stack the third cube within 60 seconds, we record the task outcome as failed and record 60 seconds as the decision time. These objective measurements allow us to analyze our first hypothesis on the influence of artificial emotions on the outcome of human-multi-robot collaboration.

After the tower construction game, we collected three subjective measurements related to participants' perception of the robots and the interaction experience. In particular, participants gave binary ratings on their perception of both robots' intelligence (capable or incompetent) and friendliness (warm or distant), as well as answering how much they enjoyed the game with a 5-interval rating from "not at all" to "very enjoyable". Previous studies have identified warmth and competence as the two main dimensions of social perception [43]. Thus, we collected binary ratings on intelligence and friendliness. These subjective measurements allow us to analyze our second hypothesis on the influence of artificial emotions on people's perception of robots and human-multi-robot collaboration.

[3]This work has been reviewed and approved by the Monash University Human Research Ethics Committee according to the requirements of *National Statement on Ethical Conduct in Human Research*, project ID 20732.

TABLE I: Artificial emotions and human-MRS collaboration.

Conditions	Success Rate	Decision Time (s)
Emotional: Role-model	62.5%	mean = 34.4, std = 25.8
Emotional: Self-centered	75.0%	mean = 15.3, std = 27.6
Non-emotional	12.5%	mean = 54.6, std = 15.2

V. Results

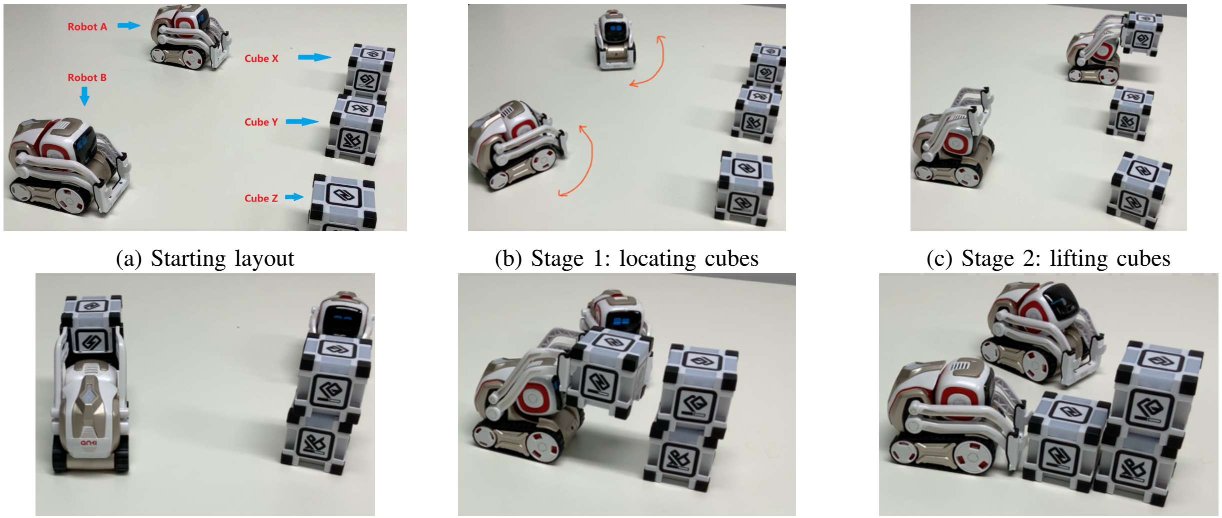
A. Artificial Emotions and Collaborative Outcomes

We report objective measurements of the tower construction game for different robot conditions in Table I. As we can see, the collaboration task has higher success rate when the robots exhibit artificial emotions. Fisher's Exact test for Role-model vs. Non-emotional conditions has $p = 0.12$; for Self-centered vs. Non-emotional conditions $p = 0.04$*. The participants spent significantly shorter time to decide to collaborate with the emotional robots. Mann-Whitney U-test for Role-model vs. Non-emotional conditions has $p = 0.046$* and the effect size measured as Cohen's d is 0.955 (large effect [44]); for Self-centered vs. Non-emotional conditions $p = 0.01$* with an effect size of 1.766 (large effect); for Role-model vs. Self-centered conditions $p = 0.03$* with an effect size of 0.715 (medium effect). Our results verified that compared to non-emotional robots, emotional robots are more likely to achieve task success in shorter time. This indicates that incorporating artificial emotions is beneficial for improving the outcomes of human-multi-robot collaboration, which aligns with our first hypothesis.

To better understand the influence of artificial emotions, we investigated two personality designs of the robots, which led to different emotional expressions at some stages of the collaborative task. An interesting observation is that robots with the self-centered personality design led to higher task success rate, as well as significantly shorter decision time, compared to robots with the role-model personality design. This may be reflecting the phenomenon that humans perceive negative emotions with high arousal values faster [45]. Thus, at stage 4 of the tower construction game (see Section IV-A), the participants may have captured the angry expression displayed by self-centered personality robots faster than the sad expression displayed by role-model personality robots. This indicates that when developing the emotional model of a robot, it is important to test different designs and to incorporate the interaction contexts.

B. Artificial Emotions and Human's Perception of Robots and Human-Multi-Robot Collaboration

We found that 87.5% participants who interacted with role-model emotional robots rated them as warm, compared to 50% in the self-centered emotional robot condition, and 62.5% in the non-emotional robot condition. Fisher's Exact test for Role-model vs. Non-emotional conditions has $p = 0.57$; for Role-model vs. self-centered conditions $p = 0.28$. As shown here, although robots designed with self-centered personality traits are more effective at enlisting human collaborators, role-model personality traits of a robot led to the impression that it is more friendly, which can be critical for



(a) Starting layout

(b) Stage 1: locating cubes

(c) Stage 2: lifting cubes

(d) Stage 3: robot A places cube X on top of cube Y, while robot B places cube Z to a location visible to robot A

(e) Stage 4: robot B attempts to place cube Z on top of cube X after interacting with robot A

(f) Stage 5: robot A attempts to enlist the participant for help after robot B fails to stack cube Z

Fig. 4: Procedure of the tower construction game.

applications requiring a positive social relationship between human and robots, such as care-taking.

In terms of participants' perception of the competence of the robots, we found that 87.5% participants who interacted with role-model emotional robots rated them as competence, compared to 75% in the self-centered emotional robot condition, and 37.5% in the non-emotional robot condition. Fisher's Exact test for Role-model vs. Non-emotional conditions has $p = 0.11$; for Self-centered vs. Non-emotional conditions $p = 0.31$. This indicates that artificial emotions lead to the impression that a robot is more intelligent and competent. Note that differences between participants' perception of emotional and non-emotional robots on their warmth and competence are not significant, which may be due to limited complexity of the collaboration task used in our experiments. Our analysis indicates that participants may perceive emotional robots more positively than non-emotional robots. However, their perception largely depends on the design of personality traits of the robots.

Regarding participants' enjoyment of the interaction session, we found that participants interacting with role-model emotional robots reported higher enjoyment (average rating = 4.4, std = 0.7) than those interacting with self-centered emotional robots (average rating = 3.5, std = 1.2) or with non-emotional robots (average rating = 3.0, std = 0.9). Mann-Whitney U-test for Role-model vs. Non-emotional conditions has $p = 0.01^*$ with an effect size of 1.637 (large effect); for Role-model vs. Self-centered conditions $p = 0.06$ with an effect size of 0.879 (large effect). This indicates that participants interacting with emotional robots report the interaction experience to be more enjoyable than with non-emotional robots, which aligns with our second hypothesis.

VI. Discussion and Conclusion

We investigated the influence of robots' non-verbal emotional expressions on human-multi-robot collaboration. By assessing objective and subjective measurements during a collaborative game between a person and two Cozmo robots, we found that emotionally expressive robots yield benefits on outcomes of human-multi-robot collaboration, as well as human's perception towards the robots.

This exploratory study can be extended in multiple directions. The multi-robot setting may have encouraged prosocial behaviors [46]; The cute, non-threatening appearance of Cozmo may also elicit more positive perception. Thus, it will be interesting to investigate the impact of these contextual factors. Note that our emotional model followed hand-crafted rules based on the appraisal theory. We plan to test other computational models of emotion that are more flexible, e.g., reinforcement learning based models [20]. Such models will allow robots to automatically learn different events' appraisal values and the emotions induced by them, and generate timely expressions in response. Our experiment is only an approximation to real-life human-robot collaboration. Therefore, we plan to conduct in-the-wild experiments, and extend this short-term HRI study to longitudinal or repeated interaction sessions. This will allow us to explore how people's perception of robots and their collaboration with robots change over time. We will also conduct experiments with a larger number of participants, which will allow us to test additional factors in human-robot collaboration, such as the perceived risk level of a collaborative task or individual differences in human collaborators.

Our study demonstrates that non-verbal emotional expressions are effective for robots to enlist help from human collaborators. Moreover, people have a more enjoyable experience interacting with emotional robots and perceive them as being more competent. Our work verifies the importance of incorporating artificial emotions for an explainable and effective human-multi-robot collaboration. Thus, researchers are encouraged to incorporate the social-emotional dimension of HRI in their future studies.

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