# Mood Estimation as a Social Profile Predictor in an Autonomous, Multi-Session, Emotional Support Robot for Children

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***Abstract*— In this work, we created an end-to-end autonomous robotic platform to give emotional support to children in long-term, multi-session interactions. Using a mood estimation algorithm based on visual cues of the user's behaviors through their facial expressions and body posture, a multi-dimensional model predicts a qualitative measure of the subject's affective state. Using a novel Interactive Reinforcement Learning algorithm, the robot is able to learn over several sessions the social profile of the user, adjusting its behavior to match their preferences. Although the robot is completely autonomous, a third party can optionally provide feedback to the robot through an additional UI to accelerate its learning of the user's preferences. To validate the proposed methodology, we evaluated the impact of the robot on elementary school aged children in a long-term, multi-session interaction setting. Our findings show that using this methodology, the robot is able to learn the social profile of the users over a number of sessions, either with or without external feedback as well as maintain the user in a positive mood, as shown by the consistently positive rewards received by the robot using our proposed learning algorithm.**

## I. Introduction

Socially Assistive Robotics is an emerging interdisciplinary field which is currently of interest to several researchers in psychology, sociology, computer science and robotics. One of the main reasons being the rapid change in the demographic structure, mostly in developed countries [1]; it is prospected that there will not be enough people to care for the weaker social groups (*e.g.* the elderly and children), both in and out of healthcare facilities in the short term.

While advances in human-computer interaction and collaborative robots have produced several methods for human and technology to interact with each other somewhat successfully (*e.g.* through touch screens and natural language understanding), Socially Assistive Robots are expected by the general public to have a deeper, more intimate understanding when communicating with their human counterparts. For this purpose, the robot must be able to get information not only from the explicit communication channels (*e.g.* words and gestures), but also from the implicit, mostly non-verbal behaviors (*e.g.* motivations and drives) of their human counterparts. Previous research [2] has indicated that autonomous cognitive and social profiling of the user are key to deploying social robots in environments outside of the laboratory (*e.g.* in hospitals, schools or at home). In order to perform this cognitive and social profiling, robots must interpret the behavior of their users through implicit cues in their facial expression and body gestures to infer mental states, personalities and emotions and, using this information, use a decision making process to determine how to best interact with a specific user.

One possible approach to achieve this preference learning is through Machine Learning techniques. However, one of the main difficulties of applying such techniques on Human-Robot Interaction (HRI) problems is the sheer amount of data required for the machine to learn anything meaningful. This is particularly harsh in HRI research for three reasons: (1) the problems addressed tend to be very application specific, (2) due to the variety of hardware and software configurations, there is yet no consensus as to what functions a social robot should or should not have and (3) due to the specificness problem, the datasets available online are scarce. Furthermore, due to the social nature of the field, it is very labor intensive to design and execute experiments to validate the hypothesis with a statistically significant number of subjects. To address these issues, we proposed [3] an implementation using an Interactive Reinforcement Learning algorithm by which a third party (*e.g.* a caregiver or relative of the user) can provide additional input to the robot through a user interface (Fig. 1), thereby dramatically increasing the ability of the robot to learn the user profile in a relatively short time while at the same time maintaining a coherent and fluent social interaction.

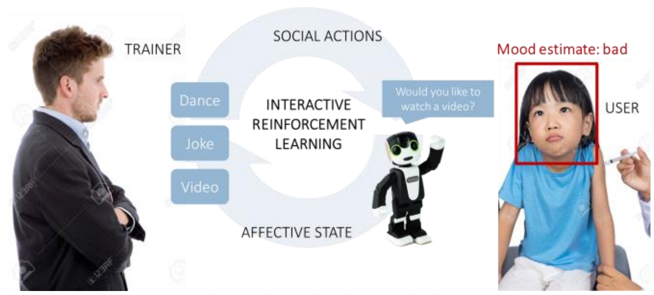


Figure 1. System Overview: The robot has a database of pre-programmed social interactions and learns from the user's affective state and the trainer's feedback through an IRL algorithm.

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As mentioned before, this work is an extension of [3], where the authors used a Wizard-of-Oz implementation to show the effectiveness of the reinforcement learning algorithm and the ability of the system to interact with real children. In addition to our previous findings, the main contributions of the present work are:

1. To develop a fully autonomous system that is able to interact with the user without the need for a remote operator.
2. The improvement of the emotion recognition algorithm and the addition of body posture as a secondary channel for learning feedback.
3. The validation of the proposed autonomous implementation through a long-term interaction experiment with 15 children.

The rest of this paper is organized as follows: In Section II, we highlight some of the related works in the field of emotional support robots. Section III describes a system overview and the methodology followed through the design of the proposed system. Section IV discusses the experiment design as well as briefly describe the interaction flow and participant demographics. Section V includes a thorough analysis of the data obtained from the experiment as well as some discussion and, finally, Section VI closes the document with a few concluding remarks.

## II. Background and Related Works

Pet therapy is a well-documented [4, 5] social therapy for people presenting symptoms of depression and isolation. In 2007, Shibata and Wada first introduced Paro – the robotic seal – in order to investigate whether a robotic pet could have similar effects to its real counterpart on the residents of an elder nursing home in Tsukuba City, Japan. Their purpose was to overcome the difficulties associated with keeping animals in delicate environments such as hospitals and nursing homes. In the results of their six-month longitudinal study [6], using tools such as social network analysis and urine sampling, they reported that the patients who actively (and voluntarily) engaged with Paro showed an increase in sociability both with other guests of the nursing home as well as caregivers. This is one of the first documented examples of using robots for social and emotional support. The main lesson to learn from Paro is that Socially Assistive Robots do not necessarily require to possess advanced cognitive understanding of the user to be effective in improving the quality of life of their users.

The ALIZ-E Project (Adaptive Strategies for Sustainable Long-Term Social Interaction) was a collaboration between several European universities and research institutions with the aim of developing a comprehensive cognitive system for robots to offer a consistent experience during long-term Human-Robot Interaction (HRI) scenarios. In particular, the project focuses on the group comprised of 8-11 years old children with diabetes for their target study. Several papers focused on solving different areas of the long-term child-robot interaction (cHRI) problem: speech, non-verbal bodily expression, small talk, gaze, touch and proximity, among others. A relevant antecedent of the present work is presented in [7], where the authors developed a high-level decision making platform between different ludic activities – collaborative sorting, creative dance and quiz – in order to engage young children over extended periods of time (over the course of a few weeks). While the robot could perform each of the ludic activities autonomously, due to limitations in the State-of-the-Art in key technologies, the robot was unable to determine when to pause/change activities (*e.g.* if the child looks bored or when there is an external interruption). Therefore, the authors used a Wizard-of-Oz interface to monitor and control the transition between activities. Their results show that by giving the child a choice of what activity they preferred to play with the robot, the kids often chose the activity they enjoyed the most, thereby increasing their willingness to interact with it for longer periods.

The team of Dr. Mataric has also published a number of papers [8-10] in relation to Socially Assistive Robots for the general public and, more specifically, with children in the school environment. Of the greatest relevance to the present work is [9], where the authors introduce their design process in creating a robot that is suitable to interact with a specific demographic (*i.e.* children). The authors highlight that in HRI implementations there must be a balance between technological prowess and domain portability. Furthermore, the authors mention that, as of yet, there are no established baseline measurements for HRI performance, with most authors reporting academic performance (*e.g.* correct responses in a quiz for a school setting) or self-reported features (*e.g.* rapport and engagement) as metrics of the platform performance. In this work, we developed a system for the robot to automatically assess the affective state of the user through interaction, with the ability to learn over time in a multi-session setting, being one of the first examples of a self-assessed, learning social robot.

Dr. Brezeal *et al*. also have a breadth of research [11-13] on human robot interaction aimed at children. We briefly highlight one of their works as background for this paper. First, Huggable [11] was a robotic companion used to mitigate anxiety, stress and pain in pediatric patients by engaging them in playful interactions. The authors presented a Wizard-of-Oz interface for a child life specialist to interact indirectly with pediatric patients. In a preliminary study, the authors aimed to determine the superiority of a robotic partner for emotional support over other types of interventions, namely a regular plush teddy bear or a virtual avatar of Huggable, with positive results.

More recently, in [2] Gunes *et al*. reported their efforts at developing HRI systems with automatic emotion and personality prediction algorithms. They reported on their experiences and lessons learned through several implementations and public HRI demonstrations. In the paper, they detail their implementation of autonomous emotion and personality predictors as cues of a user's social profile. While they note that their predictors are fully developed and describe the interaction flow and reaction of the subjects to the robot, the robotic side of their implementation is done through a Wizard-of-Oz interface. Compared to their contribution, in this work we developed a fully autonomous system using facial expression as a cue of the subject's internal affective state. Nonetheless, there are valuable lessons to learn from this publication. For example, more often than not, people would be more interested in the shape and motion of the robot than what it is actually saying, therefore they would not carefully listen to the instructions given by it and have to rely on the experimenter to successfully complete the interactions.

## III. Proposed Methodology

### A. System Overview

In this section we briefly describe the system architecture (Fig. 2) and how each part interacts with each other. In the following subsections we will further detail each module. We used a set of RGB cameras to capture the subject's facial expression and body posture in interaction with the robot. This information is used to estimate their internal affective state on-the fly as a reaction to the robot's social actions (*e.g.* dance, joke). Over time, the robot learns which of its social actions are more likely to cheer up the user when they are in a given affective state. The robot associates a user profile with their facial features for future sessions. Furthermore, although the robot can act autonomously, using the principle of Interactive Reinforcement Learning, a third party can provide additional feedback to it. This can be particularly useful when interacting with children, where visual feedback may not always be reliable due to excessive motion from the subject.

### B. Mood Estimation

Although there exists more than one proposal to model human emotions, in this work we adopt one of the most common interpretations of Paul Ekman's six basic emotions (*e.g.* joy, fear, sadness, anger, disgust and surprise). We used an in-home developed algorithm [14], which utilizes a temporal-contrastive appearance network to determine the saliency of each feature compared to a neutral facial expression. The results reported in our 2018 paper on open source databases achieved an average accuracy of 84.2%, outperforming the State-of-the-Art.

Mood is defined [15] as a long lasting affective state, usually measured qualitatively (*e.g.* good or bad mood). On the other hand, the Discrete Emotion Theory [16] poses that there exists a set of core emotions. These emotions manifest themselves through different channels (*e.g.* facial expressions, body gestures, physiological signals) in specific, discernible and unique ways. Furthermore, core emotions are semantically unique, whereas complex emotions are thought to be composed of different core emotions. Then, in mathematical terms, the set of core emotions may be described as a linear basis that spans a vector space containing the set of complex emotions. In other words, complex emotions are linear combinations of core emotions.

Based on this abstraction, we hypothesize that a good state classifier for the mood of a person can be achieved by determining whether each one of the core emotions is either low or high during a specific time interval. To achieve this, for each frame $t_i \in [t_0, t_n]$, the classifier calculates a dimension-wise mean of the pool of vectors stored up until that point. Then, if the value in time $t_i$ is greater than the current average, the emotion will be considered as high,

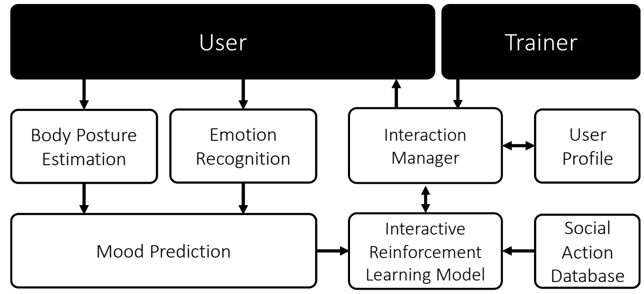



Figure 2. System Architecture

otherwise it will be low, resulting in a binary value for each time instant. The state of time interval $[t_0, t_n]$, then will be the most frequent in the post-classifier pool.

Similarly, body posture has been shown [17] to be a good predictor of engagement. In particular, head orientation and the leaning angle of the upper body are important indicators of engagement. To achieve automatic, on-the-fly engagement prediction we leverage the open source software OpenPose [18]. Using an approach similar to the temporal averaging of emotions, we can obtain an average of engagement over a certain time interval.

We then created a mapping of which states represent a good, neutral or bad mood using the following heuristic rules: Those time instants where positive emotions (*i.e.* joy and surprise) are high will be considered as good mood, time instants with only neutral emotion as high will be neutral mood, all others will be considered as bad mood. In terms of engagement, if the person is detected as engaged at each time interval, the robot will receive an additional small reward, otherwise the reward value remains unchanged.

### C. Action Database and Interaction Manager

In the context of this work, we define the actions of the robot as social behaviors that enable it to engage and interact with the child, with the possibility of having a positive impact on their mood. Examples of these actions that can be found in the recent literature [7, 19] include verbal (*e.g.* conversation, story-telling, quizzes and jokes) non-verbal (*e.g.* dance, imitation game) and complex items, such as playing games through a secondary device (tablet or computer). We propose a set of behaviors that, based on concepts from previous cHRI research (*e.g.* care-receiving robots [20]) as well as concepts from pediatric psychology (puppet therapy [21]), are likely to cheer up a child through ludic interactions and conversation.

Based on the previous survey, we defined six types of selectable interactions in this iteration of the system: joke, riddle, chit-chat, tale, dance and video. Inside each category, there were on average ten different interactions for the robot to choose from. The robot would not repeat the same single interaction twice with a given user. Each interaction included a predefined set of sentences for the robot to speak out.

Furthermore, in contrast to our previous Wizard-of-Oz implementation, in order to make the system fully autonomous, we created a behavior executor, which has basic Natural Language Processing capabilities. For example, the robot could issue a different reply depending on whether the user's response was positive or negative (*e.g.* would you like to hear a funny joke?), a predefined expected answer (*e.g.* the

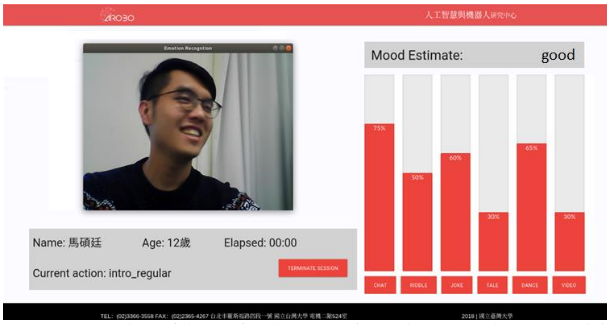


Figure 3. Screenshot of the UI for the trainer/experimenter. The personal data of the user as well as the current mood estimate can be observed. The bars to the right represent the likelihood that the robot will perform that action next.

answer to a riddle) and even save keywords from the user's utterance (*e.g.* name and gender), and use them in subsequent interactions.

### D. Interactive Reinforcement Learning and User Profiling

Briefly, what distinguishes Interactive Reinforcement Learning (IRL) from classic RL is the use of a trainer that modifies either the reward from the environment, known as reward shaping [22], the action of the agent, known as policy shaping [23] or both (hybrid approaches). In this work we propose the use of a hybrid algorithm to maximize the learning rate. Our model is built following the SARSA methodology, where the only noteworthy change in the following equation is the change/addition of the reward term:

$$Q(s_t, a_t) \leftarrow \alpha[rr_{t+1} + rp_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

The policy reward $rp_{t+1}$is designed to encourage the agent to transition from bad mood states to the good mood states and stay in good mood by providing a negative reward for a transition to a bad mood state a and a positive reward for a transition to a good mood state. The trainer reward $rr_{t+1}$, on the other hand, relies on the trainer's feedback (Fig. 3). By pressing a button, the trainer will override the next action of the robot, which will in turn modify the value of $rr_{t+1}$ for the next learning iteration. These changes are represented in real time on the bar graph.

By using the IRL algorithm, the robot stores a set of values for each state-action pair available, where the states are associated with the qualitative measurement of the user's mood (good, neutral or bad) and engagement, whereas the actions correspond to the social actions of the robot. In the literature these values are commonly known as q-values. The action selection is performed using the ε-greedy algorithm, which, for the current state, will usually pick the action with the highest q-value. However, to encourage exploration it may randomly pick other sub-optimal actions.

At the beginning of the first interaction, the robot is programmed to ask basic profile details from the user (*e.g.* name, age) and associates these data with the facial profile of the user. At the end of each interaction, the robot will save the preferences (q-values and overall reward) of the user for each interaction to persistent memory to be used in subsequent interactions. From the second interaction onward, the robot will confirm the profile of the user through dialog. This behavior was design in alignment with the findings of Fischer [24], where the authors point out that the ability of an entity to recognize users is paramount to creating social bonds.

## IV. Experiment Design

Results of our previous work showed that there was a statistically significant decrease in the negative affect of the children after playing with the robot for the first time. However, one could argue that the novelty effect [25] had a major role in the mood improvement on that pilot study. Furthermore, given the early prototype stage of the system, the control of the robot was achieved through a Wizard-of-Oz implementation. Therefore, we designed a follow-up experiment focused on the validation of a completely autonomous action selector and interaction manager for human-robot interaction and the long term effectiveness of the robot intervention for emotional support of children.

The experiment took place in the Computer and Information Networking Center, National Taiwan University. In total, 19 participants were recruited for this experiment. All participants were elementary school aged children (avg.= 10.7, σ= 1.1, 31% female). However, the data of five participants had to be excluded because they did not complete the full four sessions.

The participants enrolled voluntarily in the experiment as a part of a robotics holiday course, the parents or guardians of each student signed a consent form to participate in the experiment. The duration of this course was of five consecutive days. During each of the first four class days, each of the students was taken out of the classroom to a separate environment to perform the experiment individually. In order to avoid cross-contamination in terms of the expectations regarding the experiment, each participant was asked not to discuss the content of the experiment with their classmates until after the experiment was finished.

Two experimenters were present in each session with different roles: One would brief the participant on how to interact with the robot and perform tests to obtain a baseline of different psychologic al parameters (Section V), while the other would act as the trainer of the robot, observing the participant's reaction to the robot's actions and providing feedback through the UI (Fig. 3). Both researchers were trained on how to recognize affective states from facial expressions following the guidelines outlined in the BROMP protocol [26]. Each interactive session lasted for approximately 10 minutes. The robot deployed to perform the experiment with the child participants is RoBoHoN, a small humanoid robot smartphone. Although it does not possess top-of-the-line sensing abilities, its speech capabilities and the ability to produce body gestures through the motion of its head and arms make it an ideal candidate for human-robot interaction research.

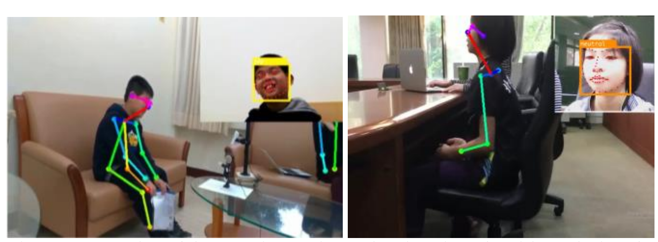


Figure 4. Samples of the emotion and mood estimation algorithms during the interactive sessions with the robot.

In addition to the robot we utilized two cameras to capture the facial expression and body posture of the participants on real time (Fig. 4). This configuration enabled the system to perform analysis and control of the robot on-the-fly with good performance.

## V. Experimental Results

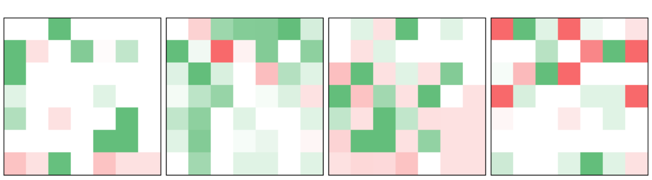
### A. Performance Metrics

To gauge the effectiveness of the system in interaction with the children we focused on the autonomous nature of the platform, relying on the rewards received by the learning algorithm through continuous interaction. As explored in Section III, there are two metrics collected by the system automatically during interaction: q-values (2-dimensional vectors) and overall rewards (scalars). Higher q-values indicate a positive reward was received for a given mood-social action combination; therefore, it follows that the actions with the highest values are considered by the robot as appropriate when the user is in a specific affective state. The reward, on the other hand, is stored as a scalar after each interaction and only the overall value after one whole interactive session is stored in persistent memory. The overall reward value is related with the perceived enjoyment of the interaction by the user, as defined by the robot itself through mood and engagement estimation or by the trainer through the rewards given.

### B. Results and Discussion

In order to determine whether the Interactive Reinforcement Learning policy had any significant effect on the user's reaction to the robot, the participant population was divided into two groups: a control group with which the robot would perform the interactions with the IRL policy as described in Section III, whereas with the other group the robot would perform the same type of interaction but without learning the user's preference, that is, picking actions randomly. In order to avoid bias from the trainer when assigning rewards to the robot, the system was programmed to randomly assign an IRL or random policy when meeting each new participant, while keeping the number of participants in each group balanced.

Due to the relatively small size of the dataset, in order to make a more significant analysis, the q-values obtained by the robot from each interaction were sorted into bad and good mood (neutral mood was grouped together with good mood). Fig. 5 shows a h eat map representation of the q-values for each policy and affective state for each user in each group. For each sub-figure, the x-axis represents one of the social actions of the robot whereas the y-axis is one of the users in that group. Darker green values represent more positive values whereas darker red values represent more negative



(a) IRL, bad mood (b) IRL, good mood (a) Random, bad mood (b) Random, good mood

Figure 5: Heat map representations of the q-values for each kind of policy.

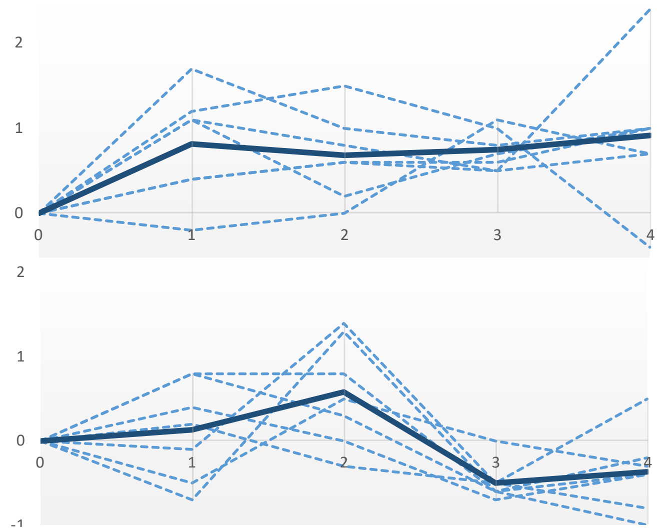



Figure 6. Comparison of the total reward by policy. The x-axis represents the day of interaction whereas the y-axis represents the reward earned by the robot from the mood estimation algorithm. The dotted lines represent the reward of each individual user, the bold line represents an average of all users with the same policy. The top graph shows the data of the group of users with the learning robot, whereas the bottom graph shows the same data for the group that interacted with a robot with random action policy.

values. Qualitatively speaking, we can observe that in the first two blocks negative values are rather scarce whereas in the latter two red areas dominate the blocks. A straightforward interpretation of this is that when the robot used the IRL policy it tended to receive more positive feedback, either from the user or the trainer, than when using a random policy. Furthermore, we can observe that certain users had an unusually high or low affinity with the robot, as certain rows in either block have a higher concentration of green or red blocks, respectively. Unfortunately, due to the small sample size we were yet unable to identify a pattern between the user's profile and their action preference.

In terms of the overall reward, Fig. 6 shows the day-by day reward obtained by the robot for all users. The dotted lines represent each individual participant's data whereas the bold line represents the average of all data points for each group, divided by the policy the robot used. Again, due to the small sample size of our test group, quantitative validation is rather difficult, so instead we provide a qualitative analysis of the graph. We can observe there is a clear difference between the tendency of each group. While in the IRL policy group the overall reward tends to increase, in the random group there is a higher variance and the overall reward is negative for almost all participants at the end of the fourth day. These findings further validate the effectiveness of the proposed IRL algorithm for extended periods of time.

## VI. Conclusions

In this paper, we outlined an end-to-end autonomous socially assistive robot for the emotional support of children. The system used an Interactive Reinforcement Learning-based methodology to learn the social profile of the users through social interactions. Under this paradigm, the robot could learn either by observing the user's reaction to its own social actions or with the assistance of a trainer, who could optionally provide additional feedback through a separate interface.

In our experiment, we had a group of elementary school children come and play with the robot. The objective of the experiment was to validate the ability of the robot to achieve long term engagement with its users, as well as to determine whether the automatic mood estimation algorithm could provide some insight into the user's social profile. To achieve this, we separated the participant pool into two groups, to compare the performance of the robot with the learning policy against a robot performing actions randomly. Results showed that there was a remarkable difference between the two groups, both in terms of preference for individual actions as well as overall for interacting with the robot. Furthermore, a cross-correlation analysis of the robot's behaviors with the profile of the user defined by questionnaires revealed that certain behaviors of the robot may exacerbate the negative feelings a person may have towards robots.

While these results are promising in terms of the effectiveness of the IRL algorithm to sustain long-term interactions with children for longer, it is yet unclear whether this algorithm could clearly define a user's social profile through sufficient interactions. Furthermore, due to the relatively small subject pool, it is difficult to draw statistically significant conclusions from these results alone. In the future, we will expand our participant pool in order to provide a quantitative analysis to further support the propose methodology.

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