



# Children’s Interpretation of Emotional Body Language Displayed by a Humanoid Robot: A Case Study

Ilaria Consoli  
Claudio Mattutino  
Cristina Gena

ilaria.consoli@edu.unito.it  
claudio.mattutino@unito.it  
cristina.gena@unito.it

Computer Science Dept., University of Turin  
Turin, Italy

## ABSTRACT

This paper presents an empirical study that examined how children interpret emotional body language displayed by the humanoid robot NAO. The purpose of the study is to provide insights into how children perceive and respond to emotional cues from robotic agents presenting an empirical evaluation that explores the effectiveness of using a humanoid robot to convey emotions to children. Through the examined results, the study aims to highlight the potential of using humanoid robots in educational and therapeutic contexts.

## CCS CONCEPTS

• **Human-centered computing** → **User models**; • **Computing methodologies** → **Cognitive robotics**.

## KEYWORDS

emotional body language, human robot interaction, affective interaction

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## 1 INTRODUCTION

The study of human communication can be divided into two main categories: verbal and non-verbal [17]. The latter encompasses a range of behaviours and gestures that are not necessarily verbal in nature. These include the use of facial expressions, gestures, posture, and other forms of non-verbal communication. Non-verbal communication is considered to be a crucial aspect of human interaction.

Some emotions are better expressed through facial expressions,

while others are better communicated through body movement or a combination of the two. Gestures can be a useful way of recognizing a user’s emotional state, especially when combined with voice and facial recognition.

There exists a consensus that both body movements and postures are important cues for recognizing the emotional states of people when facial and vocal cues are not available [1]. Emotional body language (EBL) is rapidly emerging as a new field in cognitive and affective neuroscience. According to De Gelder [6], many valuable insights into human emotion and its neurobiological basis have been gained from the study of facial expressions. In comparison, the neurobiological basis of EBL is relatively unexplored. For De Gelder [6] *EBL consists of an emotion expressed in the whole body, comprising coordinated movements and often a meaningful action, and so prompts research to go beyond facial expressions and to consider issues of perception of movement and action, which have so far been researched in isolation and not specifically related to perception of EBL*. In the field of affective computing, a machine should be able to recognise EBL and respond meaningfully to interact effectively with humans. However, in the context of Human Robot Interaction (HRI) [13], a robot equipped with arms and hands should not only be able to recognise and classify EBL, but should also be able to use EBL to express its emotions. Indeed interactive robots developed for human–robot interaction (HRI) scenarios need to be socially intelligent in order to engage in natural bi-directional communication with humans. McColl et al. [14] explored the design of EBL for a human-like social robot using a variety of body postures and movements identified in human emotion research. Experimental results showed that participants were able to recognize the robot’s emotional body language for sadness, joy, anger, surprise and boredom with high recognition rates. Beck et al. [2] reported a case study with the NAO robot interacting children whose results suggest that body postures and head position can be used to convey emotions during child-robot interaction. Their results have design implications for EBL displayed by robots. In particular they suggests that the expressivity of the negative emotions (anger and sadness) can be improved by moving the head down, while the expressivity of the positive emotion (happiness, excitement and pride) can be improved by moving the head up.

As part of our research on human-centered robot interaction, we are working on both human emotion recognition and robot emotion expression through emotional body language [5] and face



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expression [4]. In our vision, robots will be increasingly present in schools [4, 11], factories [3], and homes [12], and their empathic behaviour may foster their acceptance [10].

In particular, in one of our research projects, we attempted to reproduce gestures associated with specific emotions on a social robot, NAO [5]. We focused on Ekman's six primary emotions [8], the six universally recognised emotions, and five common emotions selected from Plutchik's Wheel of Emotions [15]. The aim of the experiment was to find out whether emotions expressed by the NAO robot through its body language could be correctly recognised and classified by users. In the current paper we describe the results of the same experiment performed this time with children, during the "Girls and boys: one day at university" events promoted by the City of Turin together with the University of Turin.

## 2 THE EXPERIMENT

In this experiment we focused on EBL and we designed a set gestures for the NAO robot associated with specific emotions. Our goal was to create easily recognizable gestures for users to associate with certain emotions. To achieve this, we conducted a guessability study where we directly asked users to associate emotions with gestures. Our references were Ekman's six primary emotions [8], along with five emotions selected from Plutchik's wheel of emotions [15].

### 2.1 Design

In determining the most appropriate body gestures to represent emotions, we consulted the Github Emotional-gesture-papers collection<sup>1</sup> and then adjusted the gestures to align with those typically observed in Italian culture [16].

A total of eleven emotions were selected, with six being Ekman's main emotions:

- (1) Disgust;
- (2) Happiness;
- (3) Fear;
- (4) Anger;
- (5) Surprise;
- (6) Sadness.

Five additional emotions were chosen from Plutchik's wheel of emotions:

- (7) Love;
- (8) Interest;
- (9) Disapproval;
- (10) Boredom;
- (11) Thoughtfulness (Pensiveness).

The total number of proposed gestures was consistently greater than eleven due to some emotions being depicted multiple times, as illustrated in Figure 1. The sensory modality most engaged in the experiment was vision, with the only limitation being the absence of sound. The exclusion of sound was implemented to emphasise the role of visual perception in participants' interpretation of EBL through robot animations. However, it is acknowledged that including the auditory sense may have accelerated participants' recognition of emotions.

For each emotion, a specific colour was associated with eye movements to facilitate identification. The colour selection process incorporated both a rational approach, considering the meaning of colours in art, and playful sources such as cartoons, exemplified by *Inside Out* [7]. The gestures and behaviours required to reproduce emotions in NAO were programmed using the robot's development environment (the NAOqi framework and the Choregraphe multi-platform desktop application within it) and triggered directly by the experimenter using the same software.

### 2.2 Subjects

Participants included a total of 176 children, comprising 86 males and 90 females. In total, nine classes were surveyed, five fifth grade classes (10-11 age group) of primary school, and four sixth grade classes (11-12 age group) of secondary school. Each class of students came separately to a lab in our department for a 2-hour tutorial in educational robotics with mBot, as described in [9]. At the end of the tutorial, the students took part in the study. Before taking part to the activities at the university, parents signed an informed consent. The study was carried out as a game with the whole class, asking the questions verbally and marking only aggregated and anonymous data.

### 2.3 Procedure

We conducted a guessability study [18], in which participants were asked to guess the emotion expressed by the NAO robot from a list of given emotions. The participants were given a list of emotions to guide them. Once the animations were presented, the participants began to watch them. The order of presentation was different from the order on the sheets, and duplicated animations were not communicated to participants to avoid exclusion or ambiguity in the results. Participants were asked all together to observe the emotions mimicked by the NAO and then try to identify them. If the response did not match the intended emotion, the participant was asked to suggest changes.

### 2.4 Results

As shown in Figure 2, the results of the experiment did not fully meet the expectations, compared to the results of our previous study [5]. There, results were quite encouraging: apart from Disgust (40%) and one version of Love (50%), participants, aged 18-34 easily guessed all the other emotions mimicked with body language.

In the current experiment with children, there was a total of 13 emotions, including duplicates. However, most of the emotions conveyed by the animations were not particularly intuitive, and some of them were ambiguous. Among all the animations, Sadness, Anger, one Happiness version 2, and Thoughtfulness were the most successful ones, probably because they were closest to the world of children, most reminiscent of comics and cartoons. All the other emotions were guessed with more difficulty, with very negative results for Interest and Surprise, which had been easily guessed in the previous experiment.

## 3 CONCLUSION

The results of the experiment described in this paper were not as satisfactory as we had expected, as they did not replicate the success

<sup>1</sup><https://github.com/mikecheninouli/Emotional-gesture-papers>

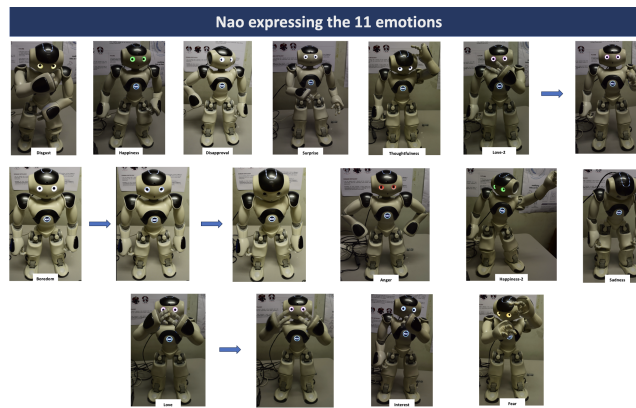


Figure 1: Nao expresses the 11 emotions, some of them are performed twice

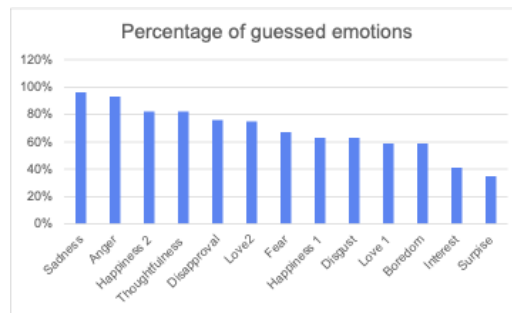


Figure 2: Experimental results of the guessability study. The percentage represents the number of participants who guessed the emotion.

of the previous experiment where, apart from the problems with the Disgust and Love associated gestures, all the other emotions expressed by Nao’s body language were guessed. This suggests that different age groups are likely to interpret the robot’s gestures differently, which could indicate that the robot’s body language should be adapted to the user’s age group. It would be interesting to repeat the experiment with older users, in the 65 and more age group. On the one hand, this prompts us to revise the body language according to the children’s suggestions, and on the other hand, to replicate the experiment with other standard age groups (teenagers, young people, adults, the elderly ) to find out if there is a correlation between age and emotional body language interpretation.

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