Social robots in learning scenarios: useful tools to improve students' attention or potential sources of distraction?

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Abstract. In this paper, we speculate about the use of social robots as convenient tools for improving learning in an educational scenario. We introduce an experimental setup in which students listen a story read by a storyteller while their attention levels are monitored through electrophysiological and behavioral measures: if the participants are judged inattentive by an electroencephalogram based measure or by the head's movements, a social robot will produce feedbacks to stimulate their attention to the shared task. We hypothesize that the participants will then realize their attention drop and will shift back their focus to the task, improving their learning. A comprehension questionnaire together with the score of a Narrative Transport Questionnaire, joined with the analysis of the collected electrophysiological data are explored to verify the effectiveness of this approach. First results with 16 adult students indicate how in learning scenarios social robots could act as a potential elements of distraction.

Keywords: Social robots in education · Sustained attention · Neurofeedback.

1 Introduction

One of the main responsibilities of teachers is motivating students towards the learning activities of the classroom through a continuous stimulation of their engagement. According to Whitton and Moseley [33], the engagement of a person in a task is based on six notions: participation, captivation, passion, affiliation, incorporation and attention. The latter is a particularly important process: it can be defined as a state in which cognitive resources are focused on certain aspects of the environment rather than on others and the central nervous system is in a state of readiness to respond to stimuli [2]. As attention can be monitored by a lot of intuitive, visible cues [5, 17], it becomes one of the main assets the teacher use to draw conclusions about students' actual engagement in learning activities. Such visible cues can "drive" the activities carried out by the classroom, with the goal of encouraging students' engagement. Goldberg et al. [17], tried to use machine learning to study such visual cues, highlighting "on-task" and "off-task" behaviors: the former, as asking questions, raising hand, taking notes, indicatives of attention; the latter, as shifting the gaze away, lying the head on the table, fooling around, connotative of inattention. Interestingly, despite the complexity on its estimation, the analysis of facial expressions resulted a better estimator of attention than head pose or gaze alone. This does not mean that the gaze and the head direction cannot provide a lot of information about attention. Blinks, time fixation, average eyes position, saccades, and pupil diameter contain information not only about the attentional phenomenon but also about the cognitive load [30]. Movements are also a good indicator of attention: if a person is, for instance, fidgeting, then he would be judged as inattentive. Furutani et al. [16] used a balance board and electroencephalography in an experiment where participants had to resolve different tasks: they noticed less the participant is attentive, more he tends to change his posture. It is important, however, to underline that the link between such visible "behavioural" cues and engagement is not straightforward: Nasir et al. [24] introduce the notion of productive engagement, stressing out that in an educational scenario, to maximize learning, engagement does not need to be maximized but optimized.

Together with behavioral cues, researchers shown how Electroencephalography (EEG) can also be used to monitor the attentional phenomenon in the brain. In particular, the literature shows that the theta/beta ratio can be exploited to evaluate the attention and the cognitive load [9, 25]. Also the beta/alpha ratio is used as engagement index in sustained attention tasks [10]. The gamma band activity alone was also assessed [22] and could be also used as an indicator of sustained attention. Experiences involving the use of machine learning shown the potentials of this approach for the classification of mental state with raw EEG data [27] and for the detection of individuals with Attention Deficit/Hyperactivity Disorder (ADHD) in a population performing an attentional task [1].

Researchers focused also on ways to enhance people attention in educational environments as well as in working places [21, 34]. In particular, the scientific literature shows that physical activities and meditation could improve attention [20, 29]. At the same time, with a similar aim, the literature proposes also the technique of neurofeedback. This technique aims at the conscious control of the brain waves by presenting to the person a real-time feedback from her own brain activity [6]. Although its effectiveness is still debated [8, 11], the neurofeedback remains interesting especially in the particular case of ADHD, with the specific goal of improving attention capabilities or working memory [12, 14].

Scientific literature proposes also the use of social robots as tools for improving attention, in particular in educational scenarios. Social robots have the flexibility of acting as tutors or as proactive learning peers, with the effect of increasing cognitive and affective outcomes [7]. Maeda et al. [19] developed a robot with the ability of encouraging children to stay focused while resolving problems, showing the potential of the robot's presence at school. Similarly, Wang and Sugaya [31] adapted the neurofeedback technique to its use with a robot able to return appropriate feedback to a student in accord to his concentration level. Interestingly, participants reported the feeling to be concentrated because they heard the robot's voice. Donnermann et al. [13] conduced an experiment with young adults and the robot Pepper. The robot gave feedback after each answers of the participant: "That's right! Well done!"; "Unfortunately that's not correct "+ [solution]. Participants reported to feel their motivation and attention increased.

In accord with this literature, in this paper we propose to explore the effects a social robot has on students' learning during an educational activity, the listening of a story. Similarly to Donnermann et al. [13] and to Anzalone et al. [3], thanks to the EEG analysis and the perception of head movements, the robot will be able to recognize attention breakdowns and, eventually, to execute appropriates feedback. We hypothesize that thanks to such feedbacks the participants will realize their attention drop and will shift back their focus to the learning task, improving the total amount of information retained during the whole activity.

2 Materials and methods

The goal of this study is to assess the impact on learning of a social robot on students in an educational scenario. We chose, in particular, to focus on a listening task, as this is one of the main activities practiced in learning environments. We propose to employ an social robot capable of promoting attention towards the shared task: the robot will be able to recognize attention breakdowns using head movements and electroencephalography; in case of attention breakdown, the robot will give a feedback using gestures and speech. We compared the effect the robot has on attention in two randomized conditions for each participant: one in which the robot is not giving any feedback (Condition A) and a second one in which the robot acts as active companion (Condition B). Questionnaires are submitted to the participants to asses the information learnt, the involvement on narrative and their perception of the robot. A free interview has been conducted with each participant at the very end of the experiment.

2.1 Experimental setup

The experience took place in an experimental room, as in Fig. 1. A small RGB-D camera, an Intel RealSense D435i[4], is placed in front of the participant that will wear a bluetooth EEG helmet with dry electrodes, an Enobio from NeuroElectrics[5]. A Nao robot, from Softbank Robotics[6] will stand in front of the

[4] Intel RealSense D435i: https://www.intelrealsense.com/depth-camera-d435i/
[5] Enobio from NeuroElectrics: https://www.neuroelectrics.com/solutions/enobio
[6] Nao robot from Softbank Robotics: https://www.softbankrobotics.com/emea/en/nao

student. The experience is recorded using a camescope. Behind a black curtain, two computers are used: one, using Microsoft Windows, for collection the EEG data; a second one, using ROS Kinetic[7] on Linux Ubuntu 16.04, for the control of the robot, for the head movements recognition and for the synchronous storage of the data. The two PC communicate between them and with the robot via Ethernet network. An hidden loudspeaker is used to spread the auditory stimulus, a story.

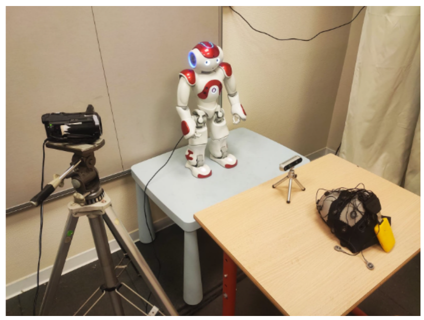

Fig. 1. The experimental setup.

Auditory stimulus The story employed as auditory stimulus is the chapter "Clochette" from the book "The Horla", by the french author Guy de Maupassant, written in 1887, available as royalty free audio book through the website Librivox[8]. This story lasts approximately 9 minutes, and was cut in 2 distinct, non randomizable, parts: Part 1, an intro, of 4min09 and Part 2, the core of the tale, of 4min39. "Clochette" was chosen because of the length, the content of the story itself and the clarity of the lecture.

Robotic platform Nao is a small humanoid robot made by Softbank Robotics equipped with audio and video sensors, able to move and communicate with voice or gestures. Nao has an interesting track record of previous experiences with children with neurodevelopmental disorders [15, 28]. A set of verbal and non-verbal, positive feedbacks made of gestures and speech were specifically developed for this experiment, such as "Interesting!" while nodding, or exclaiming "I like this!"

Head movements Participants' head movements were obtained by analysing in real-time the data from the camera. Participant's head was recognized using the library Mediapipe [9], extracting its pitch, its yaw and its position in 3D camera coordinates. Movements were inferred analysing the standard deviation of the pitch and of the yaw angles in a 0.5 sec time window: a standard deviation value continuously over a threshold during the last 5 seconds was interpreted as head movement.

[7] ROS, Robot Operating System: https://wiki.ros.org/kinetic

[8] Clochette is the story of a seamstress who becomes lame because of a man: https://librivox.org/short-story-collection-096-by-various/

[9] Mediapipe library from Google: https://mediapipe.dev/

Electroencephalography EEG analysis was performed using the Enobio-32 system through the software Neurosurfer v1.4, from NeuroElectrics[10]. In accord with the literature previously described, we focused on the use of the theta/beta ratio exploiting in real-time the data from the electrodes F3, F4, F7 and F8. A normalized attention score was calculated as average of the data from a 5 sec window [23].

2.2 Neurofeedback algorithm

The system can autonomously produce feedback through the robot, taking in account the head movements and the results from the EEG analysis [4]. In particular, while head movements could reveal shifts of the individual attention towards other elements of the environment, the theta/beta ratio can reflect mind wandering events, where the attention can drift to other thoughts. As a consequence,to take in account and capture both kind of events, a priority system has been put in place: drops of attention signalled by the theta/beta ratio have the precedence over the information from the head movements. Moreover, as a mechanism to avoid annoying closer reiterations of feedback, the system will wait 25 sec between the last executed feedback and the next one.

2.3 Questionnaires

Three different questionnaires were given to each participant, two at the end of each narration, one at the end of the interaction with the robot.

- A 7 questions comprehension questionnaire, to evaluate the information learnt by the participant, submitted to them at the end of the narration of each part of the story;
- A standardized Transport Narrative Questionnaire (TNQ) [18], to assess the phenomenological experience of being absorbed in a story [26], submitted to the participants at the end of the narration of each part of the story;
- A standardized Godspeed test [32], after participants interacted with the robot, to evaluate their perceptions.

2.4 Experimental protocol

The participant is welcomed and informed about the goals of the experience. Written consent is collected. Then he is invited to sit on the chair in front of the robot and, with the help of the experimenter, to wear a dry-electrodes EEG helmet. At the beginning of the experiment, for one minute, the signal is recorded to remove the artifacts caused by the eye blinks; then, for another minute, a baseline is built. Such baseline is produced during a short memory game, asking the participant to memorize 10 words written on a paper: the cognitive effort this task requires is not so different from listening a story and memorize information. The robot welcomes the participant and the experiment starts, following two randomized conditions: half of the participants will start with the condition A, half with the condition B. For each participant, each condition will be associated to one of the two possible chunks of the story.

[10] Neurosurfer from NeuroElectrics:
https://www.neuroelectrics.com/wiki/index.php/MediaWiki:Neurofeedback-url

Condition A, without the robot The robot informs: "You are gonna listen this part of the story. " Then it is disabled, meaning not moving at all or saying anything. The participant listen a chunk of the story. Once done, he is invited to fill out the comprehension questionnaire and the TNQ.

Condition B, with the robot The robot informs: "We are going to listen something together. I'll provide feedbacks if you are inattentive. Try to be as attentive as you can !" The participant listens a chunk of the story. In case of attention breakdown captured, the robot can adopt 2 attentive postures, says: "I'm focusing", "It's interesting", "I like this story" or "It's cool, right ?" At the end of the Condition B, the participant is invited to fill out the comprehension questionnaire, the TNQ and the Godspeed.

2.5 Participants

One of the participants was excluded because of his long curly hair which made the EEG data analysis difficult. The remaining group was composed of 16 participants: 8 men and 8 women, aged between 23 years old and 42, mean 31. 7 of them had a master degree or a PhD. They reported no diagnosis of ADHD or epilepsy and had a good comprehension of the French language. Everybody gave his/her written consent.

3 Experimental results

Collected data has been analysed via Python 3 using the SciPy library[11]. Outliers were removed before any comparison. Shapiro-Wilk test has been employed to verify the normality of the data distributions.

The statistical analysis of the comprehension questionnaire Fig. 2a, was not able to reveal any difference on the information learnt between the two conditions (Mann–Whitney U test p-value $= 0.318 > 0.05$). As pointed out by several participants during the free interview at the end of the experiment, this result could originate from a difference on the two chunks of stories listened by the participants. A statistical analysis of the comprehension questionnaire comparing these two parts revealed, as in Fig. 2b, in fact, a difference between them: the first part of the story seems slightly more difficult to comprehend than the second part (Mann–Whitney U test p-value $= 0.034 < 0.05$).

At the same time, however, the statistical analysis of the TNQ comparing the two experimental conditions revealed, as in Fig. 2c, how students are more absorbed by the story when the robot is not active (Independent samples t-test p-value $= 0.019 < 0.05$). This difference could pinpoint the robot as potential source of distraction, at least for the specific scenario took in account on this experiment.

The results from the Godspeed questionnaire (78 ± 13.5) shows the robot can be perceived as credible by the participants. These results, together with the data from the free interviews clarify the point of view of the participants

[11] SciPy library: https://scipy.org/

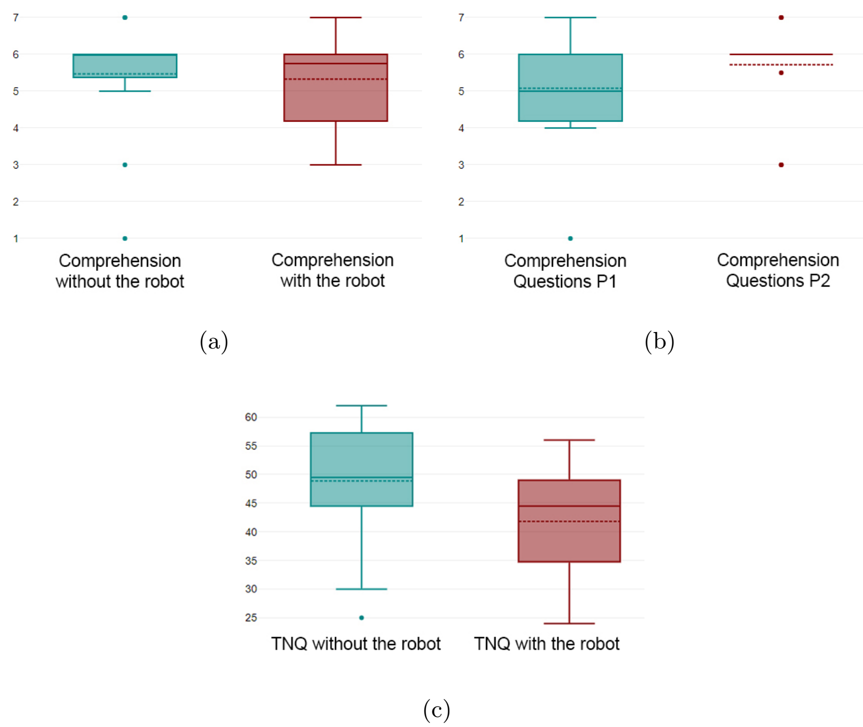

Fig. 2. Boxplot comparing the scores of the proposed questionnaires: 2a Comprehension questionnaire among the two experimental conditions; 2b Comprehension questionnaire among the two story chunks; 2c TNQ among the two experimental conditions.

regarding the presence of the robot, reinforcing the interpretation of the robot as potential source of distraction: two of them reported they tried to ignore the robot's feedback in order to better focus to the story; one of them felt judged or scolded because of the robot in front of her; three of them did not like the design of the robot while other three did; one tried to challenge the system by being inattentive while three tried to stay focused to not trigger Nao; a last one reported a real sense of presence of the robot during the experience.

Data analysis of the EEG average scores was not helpful: their comparison according to the two experimental conditions was not able to identify any difference (Independent samples t-test p-value $= 0.856 >> 0.05$). Similarly, a paired comparison of the EEG average score in a 5 sec window before against another 5 sec window after each feedback was also not able to identify any difference (Wilcoxon test p-value $= 0.928 >> 0.05$).

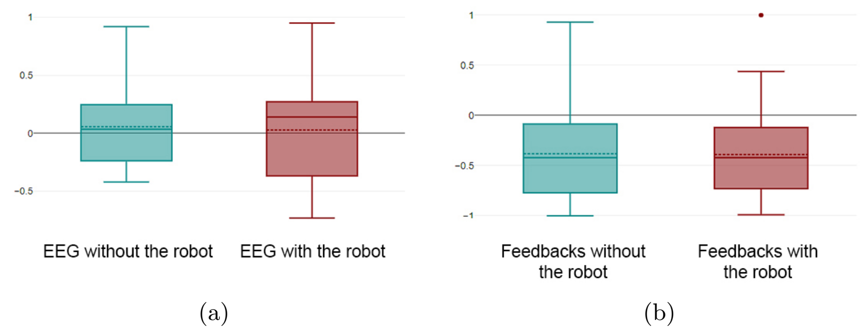

Fig. 3. Boxplot comparing the EEG scores: 3a between the two experimental conditions; 3b before against after the execution of a feedback.

4 Conclusion and future work

Results highlight the potential of a social robot as source of distraction. In the particular scenario described in this paper, the robot seemed ignored, incapable of helping students to improve their attention level. Within the limits of the small sample size of the proposed work, the experiment revealed participants that were more absorbed by the story when the robot did not interfered with the narration. However, being transported by a story does not necessarily translated to a better comprehension of the described events. It is possible to question the role of the proposed story: the length of the narration, 4 min for each chunk, maybe be not enough to reveal changes in attention for selected population; at the same time, as the first chunk of the story was judged more complex than the second one, more time may be needed by the participants to get accustomed to the proposed narration. This can be particularly important especially for the ones having a bad auditory attention. At the same time, the age of the population chosen could be a decisive factor: the effects of the use of this system by children or by adolescents could be quite different because their investment may be diverse.

The statistical analysis was not able to signal any particular difference on the EEG data. As the results from the comprehension questionnaire remain high, it is possible to hypothesize that the story was too simple for the selected population. At the same time, as some users intentionally ignored the robot while some other did not seem to see the feedbacks at all, it is also possible to imagine that participants adopted strategies to protect themselves from the robot behaviors they judged as distracting. In addition, also the metrics employed should be revised: a robot that alerts the user in the wrong moment could impact on their overall acceptance and use of the technology. Maybe, the theta/beta ratio in this scenario is not capable to capture variations on the participants' attention; at the same time, head movements not necessarily translate the attention; their combination with other metrics based, as instance, on the use of the gamma band, could improve the sensitivity of the system. More experiments focusing just on the metrics for educational scenarios should be carried on.

From the pedagogical point of view, it is possible to question the feedbacks proposed by the robot as well as the learning activity. Feedbacks were distracting or ignored: maybe, using only non-verbal back-channelling would have been enough. In any case, a balance between quiet and more communicative feedbacks should be found. About the learning task, a more appropriate alternative to the listening can be found among classical pedagogical activity. In any case, while such results question the presence of the robot in an educational environment, they can push researchers towards a deeper reflection on the pedagogy methods in presence of social robots.

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