Using Robot Adaptivity to Support Learning in Child-Robot Interaction

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Abstract. Previous research has shown that if a robot invests physical effort in teaching human partners a new skill, the teaching will be more effective and the partners will reciprocate by investing more effort and patience when their turn to teach comes. In the current study, we extend this research to child-robot interaction. To this end, we devised a scenario in which a humanoid robot (iCub) and a child participant alternated in teaching each other new skills. In the *robot teaching phase* iCub taught participants sequences of movements, which they had to memorize and repeat. The robot then repeated the demonstration a second time: in the high effort (or *Adaptive*) condition, the iCub slowed down its movements when repeating the demonstration whereas in the low effort (or *Unadaptive*) condition he sped the movements up. In the *participant teaching phase*, children were asked to give the robot a demonstration of three symbols, and then to repeat it if the robot had not understood.
The results reveal that children learned the sequences more effectively when the iCub adapted its movements to the learner, and that, when their turn to teach to the robot came, they slowed down and increased segmentation when repeating the demonstration.

Keywords: Cognitive child-robot interaction · Sense of commitment · iCub.

1 Introduction

As robots become increasingly prevalent throughout everyday life and in domains ranging from health care to education and manufacturing [5, 11, 7, 9], researchers are devoting ever more attention to developing new ways of optimizing human-robot interaction [20]. One challenge in this regard is to boost human partners' willingness to invest time and effort when interacting with a robot. Persisting in an interaction is particularly important when it involves robots endowed with learning abilities. While there is a risk of a person becoming frustrated or impatient when a robot is slow to adapt, the potential benefits of adaptation are high insofar as they can maximize a robot's ability to contribute to new tasks with new partners. Another context in which it is crucial to maintain human willingness to persist interacting with a robot is when human learning is involved. In fields of applications such as rehabilitation or education, the interaction becomes often lengthy and repetitive, but necessary to foster the desired improvements. This is likely to be an especially important challenge when children are the trainees [1, 2].

To address this challenge, Powell and Michael [14] (cf. also[15]) have recently proposed a low-cost solution based on the development of design features that could help to maintain a human's sense of commitment to an interaction with a robot. By boosting the human agent's sense of commitment, it may be possible to increase her or his willingness to remain patient and to invest effort in the interaction. To achieve this, they recommend the implementation of features that have been shown to promote a sense of commitment in human-human interaction. For example, it has been shown that, between humans, the perception of a partner's effort increases people's sense of commitment to joint actions, leading to increased effort, persistence and performance on boring and effortful tasks [22, 6, 16].

Extending this research into the context of human-robot interaction, Székely and colleagues have recently found evidence that the perception of a robot partner's apparent investment of cognitive effort boosted people's persistence on a boring task which they performed together with a robot [23]. Building upon these previous findings, Vignolo et al. have shown that if a robot invests physical effort in adapting to a human partner in a context in which the robot is teaching the human a new skill, the human partner will perform better [25] and reciprocate by investing more effort and patience in a subsequent task. In the context of child-robot-interaction, it has been shown that children are particularly willing to engage with robots that adapt their behaviours to the individual needs and abilities of the child user [1].

1.1 Aim of the Study

To verify whether a robot's apparent investment of effort into a teaching task positively impacts on children's learning, we designed an experiment in which the iCub humanoid robot and children participants alternated in teaching each other new skills. The design is inspired by [25] and adapted to make it suitable for children. In particular, the robot had to teach participants sequences of movements, by showing them with its body. Children had to memorize and repeat the sequence. In case of errors, the robot repeated the demonstration a second time. In the *Adaptive* condition the iCub slowed down its movements when repeating the demonstration whereas in the *Unadaptive* condition he sped the movements up when repeating the demonstration. We hypothesized that a higher apparent investment by the robot would improve children's performance in the training, and would increase their evaluation of the robot's helpfulness, leading them to reciprocate by investing effort to optimise their demonstrations to the robot.

2 Methods

2.1 Experimental setup

The experimental setup (Figure 1, left) consisted of a humanoid robot iCub [13, 19], a TV screen placed behind it, for showing the symbols for the *participant teaching phase*, a keyboard placed between the robot and the participants (to be pressed by them before and after the drawing to progress the experiment from one phase to the next) and a hidden RGB-D camera to monitor the experiment.

In particular, the camera was needed for the experimenter to assess if the participants repeated the sequence of movements correctly, adopting a 'Wizard of Oz' [21] paradigm. The robot's behaviour needed for the experiment was controlled with a YARP (Yet Another Robot Platform) [12] module consisting of a state machine. To make the interaction as natural as possible, we also ran a face-tracking which make the robot direct its attention on the face of the participant and we made the robot simulate blinking. The iCub's speech came out of a speaker thanks to a synthesizer and was reported also on the TV screen. Children's hand motions were recorded using an Optotrak system with an active marker on the index finger tip.

2.2 Experimental design

The experiment consisted of alternating phases:

Robot teaching phase. The robot iCub taught the participant sequences of three movements (each of them consisting of some movements of the robot's head, torso and/or arms, as in Figure 1, right), which the participant had to memorize. After the demonstration of the robot, the participant tried to repeat the sequence (Figure 1, left): in case the sequence was correctly performed, the robot would provide positive feedback and go on to the next phase; if the sequence was not correct, the robot would tell her this and repeat the sequence a second time. The participant tried again and received positive or negative feedback depending on her performance, and then continued on to the next phase.

Participant teaching phase. The participant taught the iCub sequences of three symbols (e.g. '+=?'), which appeared on the TV screen behind the robot. To teach the robot, the participant was instructed to draw the symbols in the air in front of iCub's cameras with the right index finger (left index finger if left-handed). Participants were instructed to repeat the symbols once again if the robot said he did not understand and asked for a second repetition.

At the beginning of the experiment, the participants were first provided with instructions about both tasks (i.e., for *robot teaching phase* and the *participant teaching phase*), and then asked to practice drawing the symbols in the air with their index fingers – once directed towards the robot, and then once directed towards the experimenter (or vice versa, in counterbalanced order). Then, the experimenter left them alone with the robot and a familiarization session started,

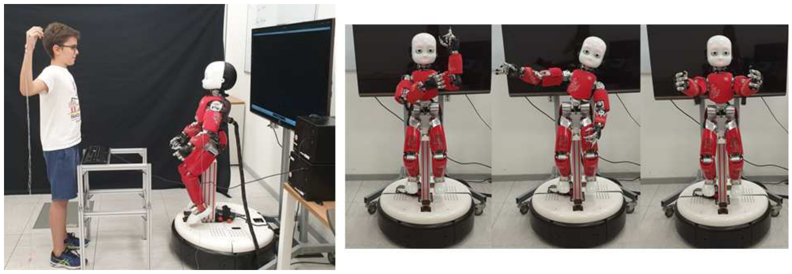

Fig. 1: Left: Participant repeating movements performed by iCub.
Right: *Robot teaching phase*: example of sequence of movements.

during which the robot said 'hi' and presented itself. As training, the participant was then asked to teach the robot a sequence of symbols, and to try to repeat a sequence of movements shown by iCub. During the experiment, in the *robot teaching phase*, two blocks with two different conditions followed each other (the order was counter-balanced among participants), with a break between them:

Unadaptive condition. If the participants did not repeat the sequence of movements correctly after the first demonstration by the robot, iCub would repeat it by speeding the movements up, using a total time of $0.75T_i$, where T_i was the duration of the sequence demonstrated the first time. In the sequence, the robot came back to the home position at a faster speed than in the first demonstration, and this made the sequence of actions appear less segmented than in the first demonstration. This behavior was meant to show that the robot was investing low effort in the training, "rushing" through the sequence of motions.

Adaptive condition. If the child did not repeat the sequence of movements correctly after the first demonstration by the robot, iCub would repeat it by slowing the movements down, using a total time of $1.39T_i$. In the sequence, the robot came back to the home position at a slower speed than in the first demonstration, and this made the sequence of actions appear more segmented than in the first demonstration. This choice was made to communicate a high effort by the robot, which invested more time in teaching.

The baseline speed (that is the speed of the first demonstration) was selected in order to make the demonstration difficult for participants to be understood at first. This was done to make the second repetition useful for the training in most trials.

Each of the two blocks consisted of six trials. Each trial was composed of one sequence of movements taught by the robot (*robot teaching phase*), and then one sequence of symbols taught by the participant (*participant teaching phase*).

At the end of each experimental block participants were asked the following question: "Did you have the impression that iCub helped you when you had difficulties in repeating the sequence of movements?" (on a scale from 1 to 5). At the end of the experiment participants were asked to answer one open question:

"What differences do you think there were in the teaching strategy of the robot in the two sessions?".

2.3 Participants

We recruited 38 participants, but the youngest 2 (the only ones of age 6) could not complete the experiment, so the final sample includes 36 participants between 8 and 16 years old (mean age 11.72 years ± 2.41 SD), 11 female and 25 male, 19 younger than 12 years old and 17 older than or equal to 12 years old. The regional ethics committee approved the protocol and all participants' parents (both) gave informed consent before the experiment.

3 Results

Among the 36 participants, 20 had the *Unadaptive* condition block first and the *Adaptive* condition afterwards, and the other 16 participants had the opposite order. The goal of the study was to investigate if a robot teacher can support children's learning of a new task by (apparently) adapting its kinematic effort, and also whether children noticed this adaptation and were aware of any effects it may have on their learning. To address these questions we compared the performances of participants between the two conditions and analyzed their responses to the questionnaires. We also wanted to see if children would modulate their commitment during their teaching phase depending on the commitment of the robot, and for doing that we compared the kinematics data of the children teaching phase in the two conditions.

3.1 Performance

Performance was calculated as the number of correct movements performed by the child, divided by the total number of movements presented (3).

After the first demonstration, performance was relatively low, especially for the younger participants. This proved that the task was not too easy to be solved, and that most participants would have needed the help of the robot to improve their memorization. Overall, 24% of the total number of trials were performed correctly already after the first demonstration.

A significant increase in performance was observed with age. Two linear regressions (Figure 2) confirmed this trend, common to both conditions (*Unadaptive*: F(1,34) = 9.54, p = 0.004, R^2 = 0.219; *Adaptive*: F(1,34) = 5.05, p = 0.031, R^2 = 0.129) However, even the oldest participants (15-16, N=6) failed to reach perfect execution (M = 0.67, SD = 0.12, significantly lower than 1 as demonstrated by a one-sample t-test, t(5) = -6.853, p = 0.001, d = -2.80, 95% CI [0.54 0.79]) and hence had margin for improvement.

After the second demonstration, performance on average improved for almost everyone (Figure 3, left). Indeed, for all participants in the *Adaptive* condition the performance after the second demonstration was higher than after the first (all

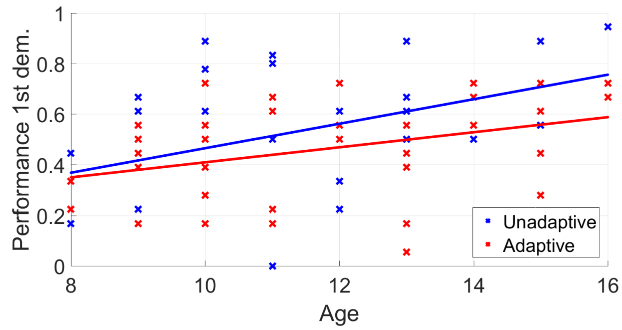

Fig. 2: Linear regression with age predicting performance after the first demonstration, for *Unadaptive* ($p = 0.004$) and *Adaptive* conditions ($p = 0.031$).

points lie above the identity line). The same held for about 86% of participants in the *Unadaptive* condition.

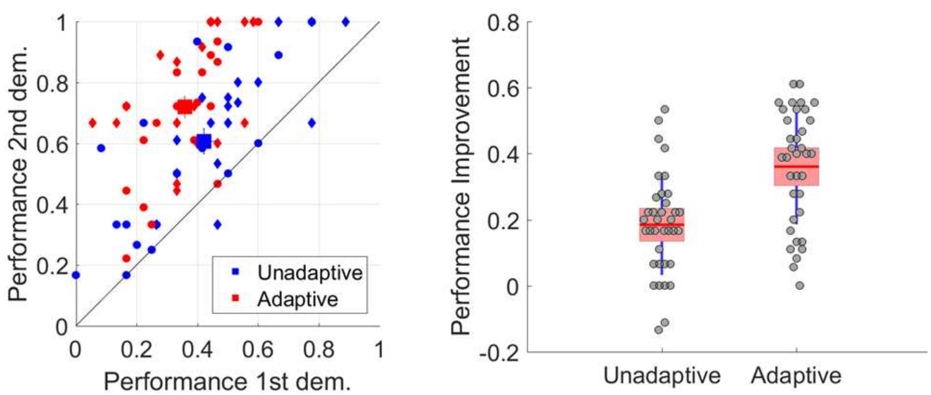

Fig. 3: Left: Individual average performance after the second demonstration plotted against the corresponding average performance after the first demonstration for the *Unadaptive* and the *Adaptive* conditions. Trials where the performance after the first demonstration was already 1 (24%) were excluded from this graph. Squares represent the averages for all the children and error bars correspond to standard errors. Circles represent children younger than 12 years old, diamonds represent children older than or equal to 12 years old.
Right: Performance improvement in the *Unadaptive* and in the *Adaptive* condition.

We computed the improvement by subtracting the performance after the first demonstration from the performance after the second demonstration.

Figure 3, right clearly shows that the performance improvement was larger in the *Adaptive* condition than in the *Unadaptive*. We checked whether this difference was significant, by controlling for potential effects of the order of conditions. The improvement of performance was submitted to a Mixed Model Anova with adaptivity (*Unadaptive* or *Adaptive*) as repeated-measures factor and block order (Unadaptive-Adaptive or Adaptive-Unadaptive) as between-groups factor. The Mixed Model Anova on the performance improvement showed that there was a main effect of adaptivity (F(1,34) = 20.639, $p < 0.001$, $\eta_p^2 = 0.230$), while no significant effect was found for order (F(1,34) = 1.80, $p = 0.189$, $\eta_p^2 = 0.020$), or for the interaction between adaptivity and block order (F(1,34) = 0.17, $p = 0.687$, $\eta_p^2 = 0.002$). Hence, participants improved their performance significantly more in the *Adaptive* condition (M = 0.36, SD = 0.17) than in the *Unadaptive* condition (M = 0.18, SD = 0.15).

In order to control for potential differences between children and early adolescents, the improvement of performance was further submitted to a Mixed Model Anova with adaptivity (*Unadaptive* or *Adaptive*) as repeated-measures factor and age group (younger than 12 or older/equal than 12) as between-groups factor. The results confirmed a main effect of adaptivity (F(1,34) = 21.72, $p < 0.001$, $\eta_p^2 = 0.233$), while no significant effect was found for age group (F(1,34) = 0.118, $p = 0.734$, $\eta_p^2 = 0.001$), or for the interaction between adaptivity and age group (F(1,34) = 1.34, $p = 0.255$, $\eta_p^2 = 0.014$).

This demonstrates that a higher effort investment of the robot enabled young children and early adolescents alike to better memorize the sequences, and thus improved their performance, independently of the order of conditions.

3.2 Questionnaires

In the questionnaires after the experiment, participants were asked what differences they found in the teaching strategy of the robot in the two sessions. Even though the experimenter explicitly said at the beginning of the experiment that there would be two different robot teaching strategies in the two sessions, 53% (19) of participants replied that there was no difference between them. 22% (8) of participants noticed a difference in the speed (one of the modifications we applied), 11% (4) in the segmentation (the other modification we applied). 14% (5) of participants replied that there was a difference in the difficulty.

Participants were then asked if they had the impression that iCub helped them when they did not understand the sequence of movements after the first demonstration (on a scale from 1 to 5).

A paired t-test showed that participants' answers to the question about their impression of iCub's helpfulness in the *Unadaptive* condition (M = 3.58, SD = 1.23) were only marginally lower from the answers given in the *Adaptive* condition (M = 3.92, SD = 1.20), $t(35) = -2.029$, $p = 0.050$, d = -0.34, 95% CI [-0.67 0.00].

We then evaluated whether the judgment of helpfulness depended on the actual improvement exhibited by each participant. A linear regression between helpfulness ratings and obtained improvements on all the data (Figure 4) was not significant (F(1,34) = 1.57, p = 0.214, R^2 = 0.022). Similar results were obtained also performing two separate linear regressions for the two conditions (*Unadaptive* condition: F(1,34) = 1.53, p = 0.225,R^2 = 0.043; *Adaptive* condition: (F(1,34) = 0.00, p = 0.978, R^2 = 2.22e-05). These results show that the participants' impression of iCub's helpfulness did not depend on their actual performance improvement.

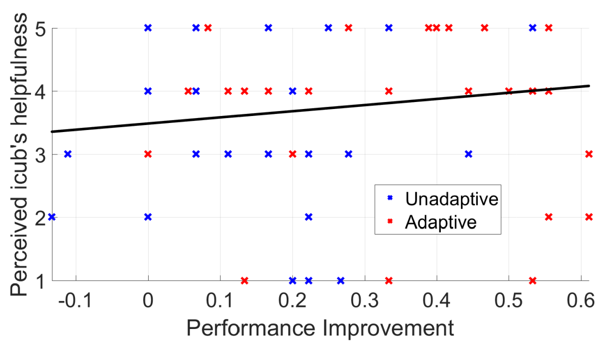

Fig. 4: iCub's helpfulness rating as a function of individual performance improvement.

3.3 Kinematic data analysis results

Kinematic (x, y, and z position) data were recorded using an Optotrak system with a marker placed on participants' index finger tip. For this analysis, 3 out of 36 subjects have been discarded as the data have not been recorded in a correct way by the Optotrak.

We computed two features to characterize the execution of the "drawing symbols" task during the *participant teaching phase*: the stroke velocity (i.e., the vertical component of the writing speed) and the pause time (i.e, the total time spent by each children pausing - with a velocity lower than a threshold defined as $th = [0.05(max(v_y) - min(v_y)] + min(v_y)$ where v_y is the vertical velocity - while writing the symbols). For each of the two, we computed the difference between the second and the first demonstration.

The differences of the kinematic data were submitted to Mixed Model Anovas with adaptivity (*Unadaptive* or *Adaptive*) as repeated-measures factor and block order (Unadaptive-Adaptive or Adaptive-Unadaptive) as between-groups factor, followed by Tukey post hoc tests.

During the second repetition of the symbol drawing, participants always slowed down to facilitate the robot's understanding; indeed, a one-tailed t-test shows that the increase of the velocity was always significantly lower than 0 (for participants that had the order Unadaptive-Adaptive, in the *Unadaptive* condition, the difference between the velocity of the second and the first demonstration was M = -47.14, SD = 35.81, $t(17)$ = -5.59, $p < 0.001$ and in the *Adaptive* condition, M = -25.95, SD = 36.96, $t(17)$ = -2.98, $p = 0.004$; for participants that had the order Adaptive-Unadaptive, in the *Unadaptive* condition, M = -27.22, SD = 34.75, $t(14)$ = -3.04, $p = 0.005$ and in the *Adaptive* condition, M = -51.59, SD = 31.11, $t(14)$ = -6.42, $p < 0.001$).

A Mixed Model Anova on the velocity differences (Figure 5, left) shows that there was a significant effect of the interaction between adaptivity and block order (F(1,31) = 14.94, $p = 0.0005$, $\eta_p^2 = 0.325$) and no order effect (F(1,31) = 0.07, $p = 0.790$, $\eta_p^2 = 0.002$) or adaptivity effect (F(1,31) = 0.07, $p = 0.790$, $\eta_p^2 = 0.002$). As can be observed in Figure 5, children slowed down more in the first block than in the second block, independently of the adaptivity.

Furthermore, children repeating the symbol drawing demonstration segmented more their actions, exhibiting longer pause times than during the first demonstration, indeed a one-tailed t-test shows that the increase of the pause time was always significantly higher than 0 (for participants that had the order Unadaptive-Adaptive, in the *Unadaptive* condition, the difference between the pause time of the second and the first demonstration was $M = 0.25$, $SD = 0.42$, $t(17) = 2.48$, $p = 0.012$ and in the *Adaptive* condition, $M = 0.20$, $SD = 0.48$, $t(17) = 1.79$, $p = 0.046$; for participants that had the order Adaptive-Unadaptive, in the *Unadaptive* condition, $M = 0.32$, $SD = 0.47$, $t(14) = 2.67$, $p = 0.010$ and in the *Adaptive* condition, $M = 0.65$, $SD = 0.44$, $t(14) = 5.68$, $p < 0.001$).

A Mixed Model Anova on the pause time differences (Figure 5, right) shows that there was a significant effect of the interaction between adaptivity and block order (F(1,31) = 4.68, $p = 0.038$, $\eta_p^2 = 0.131$) and no order effect (F(1,31) = 3.82, $p = 0.060$, $\eta_p^2 = 0.110$) or adaptivity effect (F(1,31) = 2.77, $p = 0.106$, $\eta_p^2 = 0.082$). A Tukey post-hoc test shows that participants in the *Adaptive* condition incremented the pause time significantly more if they had the order Adaptive-Unadaptive ($M = 0.65$, $SD = 0.44$) than if they had order Unadaptive-Adaptive ($M = 0.20$, $SD = 0.48$), p=0.033.

4 Discussion

Our results showed that children learned more effectively when the iCub adapted its movement kinematics to facilitate the pedagogical interaction. Slowing down the gestures and segmenting them more was indeed effective in making it easier for the children to remember and reproduce them.

Unsurprisingly, the older children performed better, but the effect of the adaptivity manipulation upon performance remained even when controlling for age (as well as for block order). We also found that more than half of the children did not consciously perceive any difference between the robot's behaviour in the

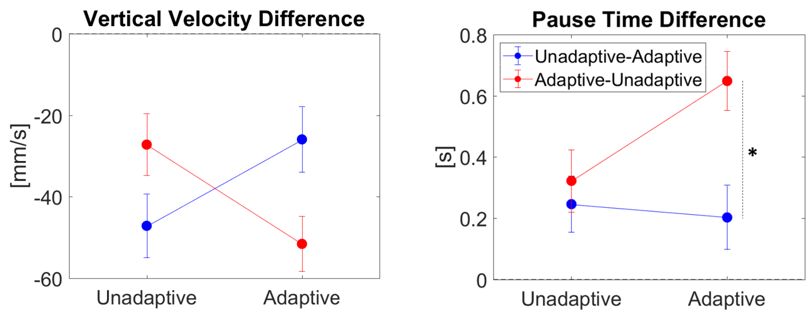

Fig. 5: Kinematic features differences.

two conditions – more precisely, when asked directly, they reported that they had not noticed any difference. However, when asked to rate the helpfulness of the robot after each block, their ratings were marginally higher in the *Adaptive* condition than in the *Unadaptive* condition. However, the judgment of helpfulness did not correlate with the actual effectiveness of the robot's teaching, i.e. with the improvement in performance obtained by the pupil.

When the time came for the children to teach to the robot, they invested effort when they demonstrated symbols to iCub: they slowed down their strokes and increased the pauses between movements when repeating a demonstration. The latter phenomenon was more pronounced when the robot itself exhibited more effort. However, reciprocation of effort was mitigated by the number of repetitions of the task. Specifically, children tended to be more adaptive to the robot during the first session. This suggests that during the relatively lengthy exercise other factors, such as boredom and fatigue, potentially had an impact on participants' behavior.

These findings build upon a wealth of research in developmental psychology which has shown that human infants benefit from spontaneous modulations of caregivers' motion properties (called "motionese" [3]). Also in our case, the slower movement and the consequent clearer segmentation of the motion proved to be effective in facilitating children understanding and replicating robot behaviors. Interestingly, previous research has explored the use of "motionese" in the context of human-robot interaction. In particular, Vollmer et al. [26] showed that human participants produce motionese when teaching to a robot. Furthermore, Nagai and Rohlfing [17] demonstrated that a robot can leverage on these movement modulations by extracting information from motionese produced by a human. In the current research we focused on the dual approach, assessing whether the execution by the robot of movements inspired by the principles of motionese had an impact on children's learning.

The current study also extends earlier research showing that children are typically very willing to treat robots as social agents [4, 18] – in particular if the robot adapts to the needs and abilities of the child [1]. More generally, our findings advance the project of designing robots that can engage with children such as to support or extend educational activities [8, 10, 24].

Further research should attempt to develop robots able to adaptively calibrate their pedagogical strategies in response to the (child and/or adult) learners' success [27]. In the current study, the changes in the robot's behavior followed a strict protocol which was determined in advance to create the impression of adaptivity while maintaining a high degree of experimental control. Moreover, it would be valuable to explore whether similar manipulations may work in other contexts (e.g. involving different kinds of effort and different tasks). Finally, it would also be valuable to explore the possibility of training children to identify differences in pedagogical approaches in order to choose demonstrations or demonstrators that more effectively facilitate their learning. Indeed, this may help them to cultivate metacognitive skills that are important for learning in general.

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