Personalising Robot Tutors’ Self-Regulated Learning Scaffolding with an Open Learner Model

Aidan Jones\textsuperscript{1}, Susan Bull\textsuperscript{1}, and Ginevra Castellano\textsuperscript{1,2}

\textsuperscript{1} University of Birmingham, UK
\textsuperscript{2} Department of Information Technology, Uppsala University, Sweden

Abstract. The ability for students to engage in self regulated learning (SRL) processes is an important factor in learning. In human-robot interaction research there is no work exploring the potential benefits of SRL scaffolding. This paper describes a study where a robotic tutor supports reflection and self-regulated learning processes with an open learner model (OLM). In this study, participants take part in a geography based task on a touch screen with different levels of adaptive feedback between conditions. An autonomous robotic tutor uses an OLM to prompt the learner to monitor their developing skills, set goals, and use appropriate tools. We see that a tutor that adapts prompts to the learner based on a model of the learner’s knowledge and rules about appropriate SRL strategies leads to significant increase in learning gain compared to control conditions where there is no support from a robotic tutor.

Keywords: Robotic Tutor, Open learner Model, Self-regulated learning, Personalisation, Human-Robot Interaction

1 Introduction

Socially Assistive Robotics (SAR) is a field in which robots aim to provide social, personalised, and long term support to people \cite{23}. One of the key domains is in education where robots can tutor students by assisting with hints \cite{21} or lessons \cite{17}.

To date robots have not been used to support Self regulated learning (SRL); SRL is the meta-cognitive process where a student uses self-assessment, goal setting, and the selecting and deploying of strategies to acquire academic skills; the use of SRL strategies are significantly correlated with measures of academic performance \cite{33}. It is important to encourage the use of SRL processes as students may not always be meta-cognitively or motivationally active during the learning process \cite{11}.

Scaffolding of SRL can be part of the feedback provided by an intelligent tutoring system (ITS); ITS that support meta-cognition can increase metacognition and learning outcomes \cite{19}. Research indicates that real time monitoring and adaptive or personalised scaffolding of help seeking behaviour within an ITS can improve student’s help seeking behaviour in the system \cite{30}.

One of the tools that can be used in an ITS to support SRL is an Open learner model (OLM); OLM externalise the model that the system has of the learner in a way that is interpretable by the learner [4]. The aims of OLM include promoting reflection, to facilitate planning and decision-making, and raise awareness of understanding or developing skills [5]. An OLM frequently takes the form of a series of skill meters [3] [22] [25]. Previous studies suggest that an OLM can help students better allocate efforts [3], improve problem selection [26], and increase learning outcomes by using an OLM as a basis for reflective self-assessment activities [22].

Research has highlighted the importance that teachers have in support for reflective and meta-cognitive processes [29]. Specifically, SRL Scaffolding can take the form of a tutor providing hints, feedback on performance, and motivating students to engage with a task [24] [1] [8]. When teachers scaffold SRL with an personalised or adaptive approach it can lead to a learner adopting better SRL skills as compared to conditions where fixed or no scaffolding was offered [2].

In the fields of HRI or SAR we see that the physical presence of a robot can also influence the learning interaction; studies that compared robotic tutors against on-screen feedback showed a preference for robotic embodiment with reference to social presence [18], enjoyment [32], trust [10], performance [11], and learning gain [21]. We have seen in our previous research that a robotic tutor can increase trust, enjoyment, and understanding in explanations of an OLM as compared to on-screen feedback alone [13]. One of the main benefits of the robotic tutor is that it can motivate students to engage in the learning activity [16] [20] [15]. As with human tutors and ITS is important to personalise the feedback, personalised feedback from a robotic tutor can lead to more successful human-robot interactions with reduced problem solving time and a more motivated learner [20].

Our novel approach is to investigate how a robotic tutor can support a learners’ SRL processes and learning gain by providing adaptive scaffolding of SRL based on the personalised feedback present in an OLM. To date there is no research looking at how a robotic tutor can support SRL.

In this study we see that a tutor that uses personalised adaptive scaffolding of SRL processes based on a model of the learner’s knowledge and rules about appropriate SRL strategies leads to significant increase in learning gain compared to control conditions where there is no support from a robotic tutor. We find that the adaptive scaffolding of SRL processes leads to significantly higher learning gains for more able students compared to static SRL prompts.

2 Scenario

The autonomous robotic tutor supports individual learners between the ages of 10 and 12 to take part in a geography task running on a touch screen. The robotic tutor is an Aldebaran Robotics NAO torso. During the study the robot sits opposite the learner and introduces the learning task and then explains how the tools work.
We have developed a map-based learning scenario that enables the learner to exhibit SRL skills and processes i.e. self-monitoring, goal setting, and help seeking. The activity is designed to test **compass reading**, **map symbol knowledge**, and **distance measuring** competencies. The learner has a choice of activities with the task of varying difficulty that allows them to practice the competencies; the menu for this is visible in the bottom left of Figure 2. The learner is provided with three tools to assist them if they are having trouble with the activity. They have the option to open a map key, use a distance tool, display a compass on screen, and to view previous clues in a scrap book, the buttons to enable these tools are in the bottom right of Figure 2.

### 2.1 Learner model and OLM

We build a learner model as the basis for the OLM skill meters and as a basis for the decision for the robotic tutor’s SRL scaffolding behaviour.

The model of the learner’s map reading competencies is created using constraint-based modelling. This is an approach whereby competency values are calculated by checking the learner’s actions against a set of relevant constraints [26]. Distance and direction are evaluated based on the learner identifying a point on a map that is a particular distance and/or direction from a starting point. Symbol knowledge is tested by selecting a particular symbol from a choice on a map. It is possible for the learner to provide a partially correct answer by meeting the distance constraint but breaking the direction and symbol constraint, this is reflected in the model with distance competency increasing and the direction and symbol competency decreasing. To ensure that the competency values are current we use a weighted average so that recent evidence is given a higher weighting than older evidence in determining the overall level of the competency.

The OLM shows skill meters for each competency and is visible at all times in the top left of the screen. Changes to the skill meters are made visible with animation and there are indicators to show the previous values [22]. The learner can inspect a history of the most recent 10 pieces of evidence for each individual competency by clicking on the corresponding skill meter. An expanded view of the OLM is shown towards the left of Figure 2. For example, if the learner expands the skill meter for distance then they will see evidence broken into north,
east, south, west; e.g. they may see that they have met the north and south constraints correctly but not the west and the east constraints. This enables the user of the OLM to see exactly in which aspect of the competency their strengths and weaknesses lie. The OLM should enable the student to plan their learning by identifying knowledge gaps, based on this they can then fill their knowledge/skill gaps by selecting an appropriate activity or tool.

Fig. 2: Expanded OLM and Learning Task

2.2 SRL Scaffolding

The aim of scaffolding SRL skills is to enable a student to develop their skills by reflecting on their current abilities, to identify strengths and weakness so that they can effectively plan their learning through selecting appropriate strategies a goals by selecting appropriate activities and using the tools and resources available. We found in a previous study that teachers scaffold SRL skills by drawing attention to the learner’s developing competencies using the OLM, then encouraging reflection on why the competencies are changing and using this as a basis to suggest appropriate tools, goals, and strategies for the learner [12]. We see that teachers would encourage the students to work in the more simple activities until they are proficient with the basic activities then work up to doing the more advanced activities. We use this approach as the basis for the Robotic tutor’s behaviours. The robot will use the OLM to prompt the learner to reflect on their developing skills and to use appropriate task strategies and work in an appropriate activity.

3 Methodology

3.1 Procedure

The study was conducted in a meeting room in the participants’ school. The activity ran on a touch screen laid flat on the table. The learner was stood up to enable them to comfortably reach all areas of the touch screen. The robot was positioned on a stand opposite the touch table in order for it to be at a similar height to the learner. We have 80 (34 female, 46 male) participants of mixed ability. The learners were aged between 9 and 12. The students were
randomly split across conditions while keeping a balance between age, sex, class, and ability.

The learner was brought in to the room, given an overview of the study and asked to complete a pre-activity questionnaire. The activity and the use of the map tools were explained by the robotic tutor. The learner then carried out the activity for 11 minutes. The participant was then asked to complete the post-activity questionnaire.

3.2 Conditions

In all cases the robotic tutor is present and gives an introduction to the task and the tools. The task gives feedback when an answer is given, the area of the task that displays the objectives flashes green if the answer given is correct or red if the answer given is incorrect.

**Personalised Adaptive SRL Scaffolding (SRL.SCAFFOLD)** In this condition the robot personalises and adapts its SRL scaffolding based on the learner’s skill levels, task performance, and rules for appropriate SRL behaviour for the current state of the learner. If the learner has displayed a high level of competence in the activity the robot highlights this by showing the evidence in the OLM, then suggest moving to a new activity. “Well done, it looks like you have mastered this, shall we move on to another activity?”. If the learner is not performing well and making mistakes the robot will highlight current state of evidence with OLM, suggest continuing with activity, potentially highlight evidence that needs to be focused on, suggest a tool, or move to an easier activity “Let’s keep going we have not covered everything in the activity” or “Let us keep going we need to focus on south” or “We need to focus on south is there a tool that can help?” or “We need to focus on south, should we do an easier task?”. We also adapt feedback based on the tool that the learner has chosen to help, If the learner selects a tool that is appropriate to their skill level and previous knowledge then they will receive encouragement and affirmation of their action “This tool should help!”. If the tool is not appropriate to the objective then they will receive a prompt to use a different tool “Is there another tool that can help you?”, if they have already demonstrated an ability with the tool then “You got this type of question correct last time, do you still need the tool?”, or if they already have a high level of competency with this type of activity “You have a good skill level for this tool, do you still need the tool?”. This is an adaptive or dynamic SRL scaffold as it provides feedback on meta-cognitive errors such as using an inappropriate tool or continuing with an activity that is too easy or too challenging [19].

**Personalised Static SRL Prompting (SRL_PROMPT)** In this personalised condition the robotic tutor offers static reflective SRL prompts that are triggered by certain actions of the learner. The robot will regularly prompt the learner to reflect on their mastery of the activity, “Do you think you have mastered this activity?”. If the learner answers incorrectly then they will be either prompted to use a tool, choose a different activity, or investigate the OLM.
randomly, “Is there a tool that can help you?” or “Should we do an easier activity?” or “Can you look at the evidence for this skill to see what you should focus on?” The feedback is still personalised as feedback is contingent on the learner’s actions, however the SRL scaffolding is considered static as it is not dependent on the state of the students metacognition as it is in the above condition [19].

**Personalised OLM with no SRL prompts (OLM ONLY)** This control condition contains feedback in the form of the OLM, after introducing the activity and tools the robot performs idle behaviours. This condition will allow us to investigate the impact of the adaptive and static SRL scaffolding over the OLM feedback.

**No feedback (CONTROL)** In this control condition the learner has no OLM and is only informed if the answer that they have provided is correct or incorrect by on-screen feedback, after introducing the activity and tools the robot performs idle behaviours.

Additionally in both SRL_PROMPT and SRL_SCAFFOLD the robot provides motivational feedback on question attempts when the learner provides a correct answer the robot produces a positive beeping noise and if the learner provides an incorrect answer the robot produces a sympathetic beeping noise.

We hypothesise that more personalised and adapted scaffolding of SRL processes via OLM will lead to higher learning gain and improving SRL processes. Adaptive SRL scaffolding will have a greater effect than static SRL scaffolding (H1), OLM alone(H2) and the control(H3) conditions. Static SRL scaffolding will will have a greater effect than OLM alone(H4) and the control(H5). Finally OLM alone will have a greater effect than the control(H6). We would expect to see these effects in less able students to a greater degree than in more able students that might already have strong domain knowledge and good SRL skills which would be similar to findings in OLM research [25].

The reasoning for this is that the OLM allows the learner to view their current and past skill levels and a history of evidence that has contributed to the skill level; this information may be used by the learner to identify strengths, weaknesses and specific areas where they have been making errors. The scaffolding provided by the robotic tutor should motivate the students to use their OLM and exercise SRL processes.

### 4 Experimental results

The results presented here are derived from the analysis of the log data and domain pre and post tests. The measures we have extracted from the logs and domain tests measure learning gain, task performance and SRL behaviours. Independent samples T-Tests were performed on the measures, we also break down the analysis to investigate differences between more able and less able students based on the mean of the pretest scores [25]. Significant differences between conditions are highlighted with a connecting black line in the figures.
4.1 Learning gain

Learning gain is the difference between a domain pre and post test scores, these tests focus on questions concerning compass reading, distance, and map symbols. Learning gain in the SRL_SCAFFOLD is significantly higher than CONTROL \((t(39)=2.007, p < 0.05)\) and OLMONLY \((t(33)=2.438, p < 0.05)\) condition both overall and with the less able students and higher than SRL_PROMPT to a non-significant degree. However we do see that SRL_SCAFFOLD is significantly higher than SRL_PROMPT \((t(22)=1.780, p < 0.05)\) for the more able students. We also see that SRL_PROMPT is higher than CONTROL and OLMONLY but only significantly higher than OLMONLY \((t(11.235)=1.858, p < 0.05)\) for less able students.

4.2 SRL indicators in task performance data

Learner model final value is the average overall learner model held by the system at the end of the activity. In the CONTROL condition it is generally lower than all other conditions. However, the CONTROL condition is only significantly lower than the SRL_PROMPT \((t(39)=1.709, p < 0.05)\) when looking at the data overall.

Number of questions answered gives an indication of how long a learner spends on each question, a learner that is reflecting more or making use of tools will complete fewer questions. In the SRL_SCAFFOLD and SRL_PROMPT the learners complete significantly less questions than the other conditions. Of the questions answered the percentage of questions answered correctly is significantly
Fig. 5: Number of questions answered higher for the OLM_ONLY condition over the CONTROL condition for less able students ($t(18) = -2.116$, $p < 0.05$).

Fig. 6: Percentage of questions answered correctly

Attempts until a successful answer measures on average how many attempts it takes for a learner to answer successfully. If this is high it is an indication that a student is not thinking carefully enough about how they are answering questions or indicates that the learner is not aware that they need to work on a skill. It is not significantly different between conditions but it is possible to see that the learners in the CONTROL condition can take far more attempts to get a correct answer particularly the less able learners. This finding is also seen in the count of the tool use which indicates that less able students without an OLM are not aware that they need to use a tool.

Fig. 7: Attempts until a successful answer
5 Discussion

There is evidence to support our hypothesis that a more personalised and adapted scaffolding of SRL processes via OLM will lead to higher learning gain and improving SRL processes.

To support H1 we see that there are higher learning gains for more able students between the personalised conditions for adaptive scaffolding and static scaffolding, this indicates that more specific prompting is needed to push more able students. We also see that the learners spend more time on each step which indicates more reflection and deliberation.

To support H2 and H3 we see that personalised adaptive SRL Scaffolding as compared to a personalised OLM alone and the control condition leads to significantly higher learning gains and more time spent on each question.

To support H4 we see that personalised static SRL Scaffolding as compared to a personalised OLM alone leads to significantly higher learning gains for the less able students and more time spent on each question in general.

To support H5 we see that personalised static SRL Scaffolding as compared to the control condition leads to a significantly higher final learner model value and more time spent on each question in general.

We see some general trends to support H6; learning gain and learner model final value do not differ significantly between the OLM only and the control condition. However, we do see that more time is taken in the OLM only. Less able students in the OLM only take significantly less steps than the control condition where they receive a significantly higher percentage of questions correctly. We also see with the less able students that that the OLM only has fewer steps to a correct answer than the control condition. This indicates that access to the OLM is important for less able students that do not have good domain or SRL skills, however we do not see that the learner taking more time translate in to increased learning gain as with the other personalised conditions.

In summary a higher level of personalisation and adaptive scaffolding of SRL can lead to greater adoption of SRL behaviours and an increase in learning gain. We also see that the OLM alone can be beneficial for less able students but loses it’s effectiveness with more able students. Adaptive SRL Scaffolding has a greater impact on more able students and may assist them in attaining higher learning gain.

6 Conclusions

The conditions with a robotic tutor scaffolding SRL appear to motivate the learners to engage in more SRL learning behaviour, the learners take more time over a question and also use tools more. For less able students it appears that any general prompts or scaffolding from a robotic tutor can help the learner engage in SRL behaviours and lead to higher learning gains to a similar degree. However for the SRL prompts to be beneficial to more able students then it
appears that greater adaption to the learner is required to increase the learning gain above the control conditions.

We feel these findings can add to the increasing amount of research in how a personalisation from a robotic tutor can assist in learning. Our approach is the first to adapt and personalise SRL scaffolding with a robotic tutor and an OLM. Other areas of research that investigate different aspects and methods of personalisation follow: a robotic tutor that provides problems that are estimated to optimise information gain to stretch a student’s ability can lead to a greater learning [7]. When a robotic tutor is personalises a hint based on a student’s skills solving a puzzle this can lead to more successful human-robot interactions with reduced problem solving time and a more motivated learner [20]. In a study where a robot personalises assistance by giving more or less specific prompts based on the ability and performance of the learner; feedback personalised in this way may be more effective and less frustrating than fully described and non specific feedback [9]. When adapting robot behaviour based on the learners engagement it is possible to increase recall levels [31]. There is increasing interest and an increasing amount of proposed research in exploring how personalisation can make HRI more effective by adapting difficulty levels [27], responding to affective states [28] [14], and learning styles [6].

The approach we use here could be applied to other educational context and age groups. The scaffolding that we use is domain independent and concerns reflection on the learner’s abilities and choosing appropriate learning strategies for the learning environment.

We see that the OLM offers benefits over the control condition, however to gain the highest advantage we need to use this as the basis to teach other SRL processes. It is not clear from this study if this same SRL Scaffolding provided by on-screen prompts or by a virtual agent would offer similar benefits. However, we have seen in our previous research that a robotic tutor can increase trust, enjoyment, and understanding in explanations of an OLM as compared to on-screen feedback alone [13]. It is also established in the field of HRI that a physical embodiment is preferred to a virtual embodiment [21].

7 Acknowledgements

This work was supported by the European Commission (EC) and was funded by the EU FP7 ICT–317923 project EMOTE (EMbOdied-perceptive Tutors for Empathy-based learning). The authors are solely responsible for the content of this publication. It does not represent the opinion of the EC, and the EC is not responsible for any use that might be made of data appearing therein.

References


