ADAPTIVE ROBOTIC TUTORS FOR SCAFFOLDING SELF-REGULATED LEARNING

by

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Abstract

This thesis explores how to utilise social robotic tutors to tackle the problem of providing children with enough personalised scaffolding to develop Self-Regulated Learning (SRL) skills. SRL is an important 21st century skill and correlates with measures of academic performance.

The dynamics of social interactions when human tutors are scaffolding SRL are modelled, a computational model for how these strategies can be personalised to the learner is developed, and a framework for long-term SRL guidance from an autonomous social robotic tutor is created.

To support the scaffolding of SRL skills the robot uses an Open Learner Model (OLM) visualisation to highlight the developing skills or gaps in learners' knowledge. An OLM shows the learner's competency or skill level on a screen to help the learner reflect on their performance. The robot also supports the development of meta-cognitive planning or forethought by summarising the OLM content and giving feedback on learners' SRL skills.

Both short and longer-term studies are presented, which show the benefits of fully autonomous adaptive robotic tutors for scaffolding SRL skills. These benefits include the learners reflecting more on their developing competencies and skills, greater adoption SRL processes, and increased learning gain.

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I would also like to thank my colleagues on the EMOTE project for their collaboration in research and writing, the lessons from which I have been able to apply to my PhD research and thesis writing.

This research would not have been possible without the participants, so thanks are due to the children, head teachers and staff at [redacted] All gave freely of their time and opinions, and their encouragement and excitement helped me to keep motivated.

My final thanks are to my family for all of their support throughout the process. I would particularly like to thank my wife Anna for holding the fort while I was gallivanting around the world at conferences. My son and daughter for providing distractions from the writing process! My mother for all of her support and introductions in finding participants for the studies and my father for many a theoretical discussion.

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CHAPTER 1

INTRODUCTION

Socially Assistive Robotics (SAR) is a field of *human-robot interaction* (HRI) in which robots are used with the aim of providing motivational, engaging, social, personalised, and longer-term support to human users in domains such as elderly care, rehabilitation, therapy for individuals with cognitive or social disorders, and education (Matarić, 2014). The support is provided primarily via social rather than physical interaction. A robot can play many different roles, for example, a social companion; carer; coach; tutor; or teachable agent. SAR is a truly interdisciplinary field that brings together a broad range of research areas, including robotics, medicine, education, social psychology, and many others (Tapus et al., 2007).

Increasingly throughout the world there are projects that explore the use of *socially assistive robots* as tutors or educational agents in educational applications (examples include EMOTE[1], EASEL[2], L2TOR[3] and CoWriter[4] in Europe; the "Socially Assistive Robotics: An NSF Expedition in Computing"[5] in the U.S.A.; and the CRR Project[6] in Japan). Motivations include providing learners with engaging learning experiences; providing learners with motivational, personalised, and longer-term support; and providing teachers with new teaching tools.

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[1]http://emote-project.eu/
[2]http://easel.upf.edu/
[3]http://www.l2tor.eu/
[4]http://chili.epfl.ch/cowriter
[5]
[6]

Most research in the area has investigated the use of robotic tutors to increase students' learning gains and engagement. While short-term studies (e.g. a single session) are relatively common (Leite et al., 2013), longer-term explorations (e.g. over weeks or months) of the effects of robotic tutors are still limited in number and scope.

Moreover, *social robotic tutors* have never been used to support *self-regulated learning* (SRL) skills. SRL is the meta-cognitive process where a student uses self-assessment, goal setting, and the selection and deployment of strategies to acquire academic skills (Zimmerman, 2008). The use of SRL strategies is significantly correlated with measures of academic performance (Zimmerman, 2008). However, it may not be easy for students to be meta-cognitively or motivationally active during the learning process (Azevedo et al., 2011), and as a consequence students will not use or develop SRL skills. If students lack SRL skills they will struggle to learn in the future, particularly if the learning task requires independent learning, is open-ended, or not well defined.

Personalised scaffolding of SRL processes by human tutors can engage the students in becoming meta-cognitively active during the learning process and leads to a greater adoption of SRL skills (Azevedo et al., 2011). Part of this effect may be due to how social factors can impact on the motivation to use SRL processes (Bandura, 1991). Within the field of *Intelligent tutoring systems* (ITS), individual components of SRL have been targeted including reflection (Bull and Kay, 2013), task selection (Mitrovic and Martin, 2003), and help seeking (Roll et al., 2011). One common way to support SRL Skills within the ITS community is to use an *Open Learner Model* (OLM), which externalises the model that the system has of the learner in a way that is interpretable by the learner (Bull and Kay, 2010). An OLM can support SRL by promoting reflection to raise awareness of understanding or developing skills, which can help planning and decision making (Bull and Kay, 2013). However, there are few studies that try to scaffold multiple components of the SRL process, which requires consideration for motivation, reflection, planning, help seeking, goal setting, and performance. Personalised social scaffolding of SRL processes does exist within ITS such as with learners teaching a virtual agent (Biswas et al., 2010) or negotiating with virtual agents (Kerly and Bull, 2008), but never with a physical robotic embodiment.

Building on results from the ITS community on SRL scaffolding, this thesis aims to close the gaps in the research on robotic tutors by exploring the use of social robots to facilitate greater adoption of SRL skills in both short and longer-term human-robot interactions.

Figure 1.1: NAO robot highlighting OLM to a primary school student

1.1 Approach and contributions

This thesis explores how *social robotic tutors* can be used to scaffold SRL skills. Firstly the thesis explores how the dynamics of social interaction can be modelled when human tutors are scaffolding SRL. Secondly, algorithms are developed for how these strategies can be personalised to the learner. Finally, a framework was created and evaluated for longer-term SRL guidance from an autonomous robotic tutor.

The aim is to support the longer-term adoption of SRL skills so that they are adopted as a general behaviour; longer-term behaviour change is also one of the aims in SAR (Matarić, 2014) and ITS (Koedinger et al., 2009) research. To achieve this aim initial pilot studies explore how a learner can be engaged and motivated to learn, further studies then explore how this support can be carried forward through longer-term interactions. This approach can be summed up with the following research questions:

- **RQ1:** Can a robotic embodiment impact the perception of an OLM and encourage a learner to reflect on their skills?
- **RQ2:** Can a robot computationally detect and model reflection and SRL skills of a learner in real time? Can this computational model be used to improve the personalisation and adaptability of a robotic tutor?
- **RQ3:** Does the personalised SRL scaffolding delivered by a robotic tutor impact learners' perception of the robot, activity, motivation, SRL skills and learning gain in both short-term and longer-term interactions?

This thesis describes the development of a fully autonomous robotic tutor and touchscreen based geography learning scenario that allows 10 to 12 year old children to demonstrate and develop their SRL skills. A NAO robot[1] is used as the *social robotic tutor*. In all studies the robotic tutor is fully autonomous as opposed to being controlled by a human "wizard" (Dahlbäck et al., 1993). The interaction between the autonomous robotic tutor and the learner is supported by having the robot sit opposite the learner over a touchscreen table on which the geography activity is running. Both the autonomous robotic tutor and learner can control aspects of the activity as needed. This approach allows the robot to respond in a consistent manner to different learners. It is also essential to enable the analysis of the effectiveness of the computational model of SRL and the robots adaptive support to the learner. In

[1]https://www.aldebaran.com/en/humanoid-robot/nao-robot

addition there is no need to deceive the learner about the capabilities of the robotic tutor.

A *user-centered design* (UCD) approach is followed, involving the teachers and learners at every stage of development. The UCD studies elicited requirements that were used to create a systems specification, which then informed the design and implementation of the learning scenario and robotic tutor. The UCD studies as set out in Table 1.1 and Table 1.2:

Study 1: teacher interviews (section 3.4). Interviews with teachers to understand how a robot should fit in to the classroom, which informed the specification of the learning scenario and how a robot tutor could interact with learners.

Study 2: mock-up study (section 3.5). Mock-up studies where a teacher was observed supporting individual learners at an early stage of learning scenario development, which further informed the specification of the learning scenario, OLM, and the robotic tutor's behaviours.

Study 3: embodied OLM study (section 3.6). As a robot is inherently different from a human on many levels, studies were conducted to investigate how learners perceived skill based feedback from different levels of embodiment, which further informed the specification of the learning scenario, OLM, and the robotic tutor's behaviours.

Study 4: UCD teacher study (section 3.7). Observation of an experienced human teacher using the OLM to provide SRL support to learners. Successful personalised tutoring has to attempt to identify pedagogical strategies that are most effective in establishing, strengthening, and sustaining social bonds and supporting SRL behaviour. Which further informed the specification of the OLM, and the robotic tutor's behaviours.

The studies were based in the learner's school to ensure that the meta-cognitive interaction would be valid in a school environment (Koedinger et al., 2009). Based on these studies, the final learning scenario, the computational model, and robotic behaviours that the fully autonomous robotic tutor uses to scaffold SRL skills were developed. The computational model to adaptively scaffold SRL skills details how a robotic tutor uses the OLM to encourage reflection on the learners' changing skills and competencies as a basis to suggest appropriate tools, goals, and strategies for the learner. The computational model is used for robot personalisation that adapts to support the learner's domain knowledge and SRL skills. The fully autonomous robotic tutor was then evaluated.

Study 5: adaptive SRL study (section 6.2). The fully autonomous robotic tutor was evaluated in a short-term study to see how different levels of personalisation of SRL scaffolding affect SRL skill tutoring and how this impacts learning gain and quality of interaction.

Study 6: longer-term SRL study (section 6.3). A longer-term study was performed to investigate effects of SRL tutoring compared to standard domain tutoring to assess the different impact on SRL skills, learning gain, and quality of interaction. The robotic tutor's scaffolding of SRL skills was enhanced by a memory of previous interactions with the learners, which enabled the tutor to give a summary of developing skills to further support reflection and enhance the social interaction.

By following this approach in answering the research questions the following contributions have been made:

Contribution 1. How a robotic tutor's embodiment can best be used to support SRL skills. As OLM are commonly used in ITS to promote reflection, an investigation was made in to how best a *social robotic tutor* can support a transparency system to the underlying model that the system holds. The transparency approach involves displaying feedback on the screen as an OLM visualisation and using the robot to highlight pertinent details. The novelty is how the robot with an OLM can co-regulate SRL with the robot's behaviours and feedback. It was found that the use of a *social robotic tutor* to support the presentation of the model had beneficial implications for engagement and trust in the model.

Contribution 2. Developed a computational model of SRL scaffolding based on *human-human interaction* (HHI) studies and literary review. This model allows adaptation based on the learner's domain knowledge and SRL skills. Ways to measure SRL skills and behaviours by the learner in real time were identified. This holistic approach to SRL scaffolding does not just look at one aspect of SRL but a number of components, such as motivation, reflection, planning, help seeking, goal setting, and performance. This approach enables the investigation of how a robotic tutor could adapt support to an individual in order to scaffold these skills: more adaptive scaffolding of SRL skills leads to greater learning gain. It was also observed that if the robotic tutor does not provide specific help while scaffolding SRL skills, then the SRL skills are not likely to be adopted by the learner who may become disengaged. This appears due to an increase in the pressure and tension in the activity, and a decreased perception of the robotic tutor.

Contribution 3. How to evaluate a robotic tutor scaffolding SRL skills. By exploring how the robot used social affordances to engage and motivate a learner to utilise SRL skills in educational scenarios, this brings together the benefits of social robots to the ITS field. Both short-term and longer-term studies were conducted to evaluate the fully autonomous robotic tutor. The considerations that were needed to select appropriate metrics for the studies are also presented. Overall, the studies demonstrate how a robotic tutor can support the transfer of SRL skills by using memory and a summary of developing skills to support a longer-term interaction. It can seen that the effects are not necessarily short lived or due to a novelty effect.

Contribution 4. A UCD design approach can be used to develop and evaluate a *social robotic tutor* that takes into account the needs of the teachers and learners. It is shown that the *social robotic tutor* is effective in scaffolding SRL in a real world school environment. The UCD approach that has been followed could be used by robotics researchers to further develop *social robotic tutors* in other domains. The key factors of this approach that may lead to longer-term behaviour change are:

using studies based in the real world school environment; using a physical robotic embodiment; basing pedagogical and social behaviours on human teachers; and using behaviours that adapt to the learner to provide personalised support.

The links between the studies, research questions and contributions are presented in Table 1.1 and Table 1.2.

Table 1.1: Table of Studies (a): presents the links between the studies, research questions, and contributions

Study Name	Description	RQ	Contribution
Study 1: teacher interviews (section 3.4)	Interview with teachers about role of robotic support	RQ1	• Contribution 4. Understand requirements to meet needs of teachers and learners.
Study 2: mock-up study (section 3.5)	Pilot study where a teacher supported a learner through a paper based activity.	RQ1	• Contribution 4. Understanding needs of teachers and learners in the learning scenario. Allowed development of activity where learners can demonstrate SRL skills essential for real time modelling.
Study 3: embodied OLM study (section 3.6)	Explore effect of robot embodiment on perception of OLM.	RQ1	• Contribution 1. Engagement and trust greater when some items are displayed onscreen and some feedback given verbally by robot. Shows balance of how much OLM should be provided through robot. • Contribution 3. Understand how to evaluate a robotic tutor in short-term study. • Contribution 4. Understanding needs of learners.

Table 1.2: Table of Studies (b): presents the links between the studies, research questions, and contributions

Study Name	Description	RQ	Contribution
Study 4: UCD teacher study (section 3.7)	Observation of an experienced human teacher using the OLM to provide SRL support to learners.	RQ2	• Contribution 2. Provided basis of how the robot uses OLM to motivate and personalise SRL support. • Contribution 4. Understand the needs of teachers and learners.
Study 5: adaptive SRL study (section 6.2)	Explore different levels of personalisation with robotic tutor	RQ3	• Contribution 3. Adaptive support leads to greater SRL behaviours and learning gains. Highlighting issues but not providing sufficient level of support makes the learners feel higher levels of stress and pressure and cause them to become disengaged. • Contribution 4. Understanding needs of learners.
Study 6: longer-term SRL study (section 6.3)	Comparison between adaptive SRL scaffolding with domain support and a robot with adaptive domain support	RQ3	• Contribution 3. Longer-term SRL support can have an effect on self report of SRL attitudes.

1.2 Structure

This thesis is organised as follows. In *chapter 2* the relevant background material on SAR, *social robotics* in education and SRL is summarised. In *chapter 3* the UCD approach is described including the design goals, research questions and iterative design process. In *chapter 4* the systems specification, technical development, and implementation of the learning scenario, the learner model, the OLM, and fully autonomous robotic tutor are detailed. In *chapter 5* the computational model that is used for robot personalisation that adapts to support a learner's domain knowledge and SRL skills is described. In *chapter 6* the short-term and longer-term studies to evaluate the fully autonomous robotic tutor and computational model of SRL are described. In *chapter 7* the thesis is concluded with a discussion of the key contributions, detailing how a robotic tutor can scaffold SRL and how this can impact on child learning.

1.3 Ethics Statement

[redacted]

1.4 Publications

During the writing of the PhD the author has written or contributed to a number of papers. Below is a list of the papers with details of how they are related to the research presented in this thesis. The following journal, workshop, or poster papers were written with the author's PhD supervisor's support and describe the work undertaken for the thesis.

- Jones, A. and Castellano, G. (2018). Adaptive Robotic Tutors that Support Self-Regulated Learning: A Longer-Term Investigation with Primary School Children. *International Journal of Social Robotics*, pages 1–14 (Jones and Castellano, 2018). This journal paper describes the longer-term (4 sessions over 1 month) study (section 6.3) that compares personalised adaptive SRL scaffolding to personalised domain support.

- Jones, A., Bull, S., and Castellano, G. (2017b). I Know That Now, I'm Going to Learn This Next Promoting Self-regulated Learning with a Robotic Tutor. *International Journal of Social Robotics*, pages 1–16 (Jones et al., 2017b). This journal paper describes the short-term study (section 6.2) that investigates different levels of personalised SRL support.

- Jones, A., Bull, S., and Castellano, G. (2015a). Personalising Robot Tutors' Self-Regulated Learning Scaffolding with an Open Learner Model. In *First International Workshop on Educational Robots (WONDER), International Conference on Social Robotics (ICSR)* (Jones et al., 2015a). This workshop paper describes the short-term study (section 6.2) that investigates different levels of personalised SRL support.

- Jones, A., Bull, S., Castellano, G., and Descriptors, S. (2015c). Open Learner Modelling with a Robotic Tutor. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts*, pages 237–238. ACM (Jones et al., 2015c). This was a presentation at the HRI Pioneers workshop in the HRI conference poster session. It describes the results of the embodiment study (section 3.6), and the plan for the teacher OLM study and the longer-term study.

- Jones, A., Bull, S., and Castellano, G. (2015b). Teacher Scaffolding of Students' Self-regulated Learning using an Open Learner Model. In *Demos and Poster Proceedings (UMAP 2015)* (Jones et al., 2015b). It describes the studies performed with teachers (section 3.7) and how the teachers prompted the SRL skills within the learning scenario with the OLM.

- Jones, A., Castellano, G., and Bull, S. (2014b). Investigating the effect of a robotic tutor on learner perception of skill based feedback. In *International Conference on Social Robotics*, pages 186–195 (Jones et al., 2014b). It describes the findings from the study on embodiment of skill based feedback (section 3.6).

- Jones, A., Bull, S., and Castellano, G. (2014a). Open Learner Modelling with Social Robotics (Jones et al., 2014a). It presents the intended direction of the PhD at this point.

- Jones, A., Bull, S., and Castellano, G. (2013). Teacher Perspectives on the Potential for Scaffolding with an Open Learner Model and a Robotic Tutor. In *AIED 2013 Workshops Proceedings Volume 2 Scaffolding in Open-Ended Learning Environments (OELEs)*, page 29 (Jones et al., 2013). This paper considers the potential for scaffolding learning in an open-ended learning scenario using a robotic tutor and an OLM based on interviews with teachers.

While undertaking this PhD the author worked on the design and development of the social robotic tutor for the EMOTE project. Though the below papers were written for the EMOTE project, they are relevant to this thesis given that the UCD design process and development of the learning scenario that is presented here was also used as a basis for some of the studies in the EMOTE project. The robotic tutor developed for the EMOTE project was very different to the robotic tutor in this thesis, the focus in the EMOTE project was to adapt to the affective states of the learner and did not investigate SRL at all. The author worked with the co-authors on the design, development, evaluation, and write-up of the following studies. The design and implementation of the task and the research in this thesis is the authors work, where ideas have been used from the EMOTE project they have been appropriately referenced in the thesis. :

- Jones, A., Dennis, K., Basedow, C. A., Alves-oliveira, P., Serholt, S., Hastie, H., Corrigan, L. J., Barendregt, W., Kappas, A., Paiva, A., and Castellano, G. (2015d). Empathic Robotic Tutors for Personalised Learning: A Multidisciplinary Approach. In *International Conference on Social Robotics*, volume 1, pages 285–295 (Jones et al., 2015d). The author of this thesis was the lead author on this paper which described the design and development of the EMOTE system as a whole.

- Barendregt, W., Serholt, S., Alves-oliveira, P., Jones, A., and Paiva, A. (2017). (Under Review). Students' Perspectives on Tasks, Responsibilities and Characteristics of Classroom Robots. *International Journal of Social Robotics* (Barendregt et al., 2017). This journal paper is in submission; it describes students' perspectives on education robotics. The author of this thesis helped conduct the presentations and questionnaires used in this paper.

- Serholt, S., Barendregt, W., Vasalou, A., Alves-Oliveira, P., Jones, A., Petisca, S., and Paiva, A. (2016b). The case of classroom robots: Teachers' deliberations on the ethical tensions. *AI & SOCIETY*, pages 1–19 (Serholt et al., 2016b). For this journal paper the author of this thesis interviewed teachers and provided input on the writing.

- Serholt, S., Barendregt, W., Küster, D., Jones, A., Alves-Oliveira, P., and Paiva, A. (2016a). Students' Normative Perspectives on Classroom Robots. In *Proceedings of the International Research Conference Robophilosophy* (Serholt et al., 2016a). This was presented at the Robophilosophy conference in 2016. The author of this thesis helped conduct the presentations and questionnaires used in this paper and also gave input on the writing.

- Deshmukh, A., Jones, A., Janarthanam, S., Foster, M. E., Ribeiro, T., Corrigan, L. J., Aylett, R., Paiva, A., Papadopoulos, F., and Castellano, G. (2015a). Empathic Robotic Tutors: Map Guide. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts*, page 317923. ACM (Deshmukh et al., 2015a). This paper was presented as a demonstration at the Human-Robot Interaction (HRI) 2015 conference. The author of this thesis was involved in the development of the learning scenario and also development of the architecture presented.

- Deshmukh, A., Jones, A., Janarthanam, S., Hastie, H., Ribeiro, T., Aylett, R., Paiva, A., and Castellano, G. (2015b). An Empathic Robotic Tutor in a Map Application. In Bordini, Elkind, Weiss, and Yolum, editors, *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015)*, pages 1923–1924, Istanbul, Turkey (Deshmukh et al., 2015b). This paper is similar to the "Empathic Robotic Tutors: Map Guide" paper.

- Hall, L., Hume, C., Tazzyman, S., Deshmukh, A., Janarthanam, S., Hastie, H., Aylett, R., Castellano, G., Papadopoulos, F., Jones, A., Corrigan, L. J., Paiva, A., Oliveira, P. A., Ribeiro, T., Barendregt, W., Serholt, S., and Kappas, A. (2016). Map Reading with an Empathic Robot Tutor. In *International Conference on Human-Robot Interaction, Christchurch, New Zealand, Extended Abstracts* (Hall et al., 2016). This paper was presented as a demonstration at the Human-Robot Interaction (HRI) 2016 conference. It is similar to the

"Empathic Robotic Tutors: Map Guide" paper.

- Ribeiro, T., Alves-Oliveira, P., di Tullio, E., Petisca, S., Sequeira, P., Deshmukh, A., Janarthanam, S., Foster, M. E., Jones, A., Corrigan, L. J., Papadopoulos, F., Hastie, H., Aylett, R., Castellano, G., and Paiva, A. (2015). The Empathic Robotic Tutor: Featuring the NAO Robot. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts*, page 285, Portland, OR, USA. ACM (Ribeiro et al., 2015). This paper was presented as a video at the Human-Robot Interaction (HRI) 2015 conference. It focuses on the scenario 2 learning scenario from the Emote project with which the author of this thesis was involved.

- Serholt, S., Barendregt, W., Leite, I., Hastie, H., Jones, A., Paiva, A., and Castellano, G. (2014a). Teachers' Views on the Use of Empathic Robotic Tutors in the Classroom. In *RO-MAN 2014* (Serholt et al., 2014a). It describes interviews with teachers undertaken as part of the EMOTE project. The author of this thesis assisted with the design of the interview itself and administered some of the interviews.

- Ribeiro, T., Tullio, E., Corrigan, L. J., Jones, A., Aylett, R., Castellano, G., and Paiva, A. (2014). Developing Interactive Embodied Characters using the Thalamus Framework: A Collaborative Approach. In *Intelligent Virtual Agents*, pages 364–373 (Ribeiro et al., 2014). The author of this thesis helped adapt the *Thalamus Framework* to the EMOTE project.

- Papadopoulos, F., Corrigan, L. J., Jones, A., and Castellano, G. (2013). Learner Modelling and Automatic Engagement Recognition with Robotic Tutors. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*, pages 740–744. IEEE (Papadopoulos et al., 2013). It describes the early work on learner modelling and affect detection in the EMOTE project that the author of this thesis helped to develop.

CHAPTER 2

BACKGROUND

This chapter reviews the relevant literature around SAR and how SAR robots are used in education scenarios. The literature on SRL and how SRL is scaffolded by teachers and ITS is then reviewed before concluding this background chapter by suggesting how a *social robotic tutor* may be able to scaffold SRL processes.

2.1 Socially assistive robotics

SAR is a field in which robots aim to provide motivational, engaging, social, personalised, and longer-term support to people (Gordon and Breazeal, 2015; Tapus et al., 2007; Fasola and Matarić, 2013; Matarić, 2014; Feil-Seifer and Matarić, 2005; Clabaugh et al., 2015). The field of SAR lies at the intersection of the fields of *Assistive Robotics* and *Socially Interactive Robotics* (Feil-Seifer and Matarić, 2005). In *Assistive Robotics* a robot's main function is to support people through physical contact, often for purposes of physical rehabilitation (Feil-Seifer and Matarić, 2005). In *Socially Interactive Robotics*, a robot's main function is to have social interaction with people; the goal is to create a good interaction rather than offer physical support (Feil-Seifer and Matarić, 2005; Fong et al., 2003). The goal with SAR is for a robot to support people through non-physical social interaction (Feil-Seifer and Matarić, 2005), as such this brings together a broad range of research to ensure that this non-physical support is relevant to the needs of the target population (Tapus et al., 2007).

2.1.1 Applications of socially assistive robots

Due to complex interplay of social interactions and supportive behaviours between the robot and user there are many factors to take into account in the design, development, and evaluation of a *socially assistive robot*. Below some examples of the domains and user populations that *socially assistive robots* can support are discussed, including the roles that the robot can take to provide effective support in those domains.

Elderly care

The elderly are a group of people with specific needs that SAR aims to support. It is hoped that robots can help the elderly retain independence for longer and also offer assistance with mental health issues (Broadbent et al., 2014; Chang and Šabanovi, 2015; Orejana et al., 2015; Feil-Seifer and Matarić, 2005; Roy et al., 2000; Lehmann et al., 2013; Jenkins and Draper, 2014)[1].

Support can be in the form of social support, such as PARO, a seal shaped therapeutic robot, whose role is to be that of a pet. This robot has been used to improve mood, reduce stress, and encourage social interaction (Chang and Šabanovi, 2015; Aminuddin et al., 2016). The support can be in the form of guidance via a mobile robot, such as Nursebot Pearl (Pineau et al., 2003). This is a large mobile robot that can provide the elderly and their nurses help with day to day activities by reminding the users to take medication and guiding the user around the environment. SAR can also support rehabilitation, which is discussed in the next section.

The ultimate goal is for a mobile robot to be able to assist with some physical needs while a social element will also assist with the acceptance of the robot into

[1] http://accompanyproject.eu/

that role.

Studies have shown a good level of social acceptance of robots supporting the elderly in longer-term interactions (Orejana et al., 2015; Broadbent et al., 2014). However, care is needed in the design and robustness of these robots or it may not lead to significant increases in measures of quality of life or medication adherence (Broadbent et al., 2014).

Health-care and rehabilitation

Another group that SAR can benefit is patients in convalescent care e.g. patients that need some assistance with physical therapy (Feil-Seifer and Matarić, 2005). These robots build upon the work of social agent coaches to motivate the users to perform their physical therapy (Fasola and Matarić, 2013). Non-social physical robots have shown a great deal of success in rehabilitation after strokes (Lo et al., 2010) and there is potential to use a social element to improve the effectiveness of these robots by making the therapeutic process more enjoyable (Matarić et al., 2007). Robots can also provide social support by distracting and engaging users while they are recovering in hospital (Saldien et al., 2006).

Cognitive disorder or social disorders

Socially assistive robots are used to support people with cognitive and social disorders such as *Autism Spectrum Disorder* (ASD) (Dautenhahn and Werry, 2004). Robots are used to support the development of life skills to allow the user to lead a more independent life and reduce behaviours that could interfere with this (Begum et al., 2016). The KASPAR robot has been used to help users with ASD develop social and communication skills (Robins et al., 2012; Wainer et al., 2014). There are a number of robust longer-term studies that show that robotic intervention can have lasting effects even when the robot is no longer present (Wainer et al., 2014; Robins et al., 2005). It may also be possible for personal service robots to safeguard and support users with memory difficulties (Roy et al., 2000).

Child robot interaction

SAR projects are often aimed at supporting children; this field is normally referred to as cHRI (Belpaeme et al., 2013). In order to develop cHRI systems it is essential to have a good understanding of the differences between how a child and how an adult view the world and specifically their perception of robots, e.g children may view robots as social entities far more quickly (Kahn et al., 2015). The Keepon robot is an example of a minimal robot that is able to build social bonds with children through contingent non-verbal behaviours that include eye contact, joint attention, and basic expression of affect (Kozima et al., 2008).

As with elderly care there have been a number of *social robotic* animals developed as pets or companions using the Aibo or Pleo robotics platforms (Leite, 2013). The robots are also used to support children with health care issues (Saldien et al., 2006) and with cognitive disorders (Feil-Seifer and Matarić, 2005).

Robots in education

Socially assistive robots are increasingly being used in education e.g. the "Socially Assistive Robotics: An NSF Expedition in Computing" (Scassellati, 2016). This section will not discuss educational robotic activities where students learn how to program a robot (Catlin, 2013). This section will address how a social robot can be used as an agent in education. It is believed that the formation of a socio-emotional relationship between the learner and robot is paramount to facilitating a good learning experience (Jones et al., 2015d). There are a number of studies that investigate longer-term interaction with robots in education and show high levels of social acceptance and engagement (Leite et al., 2013; Tanaka et al., 2007).

The robots can be used as *social robotic tutors* that act as educational agents or teaching assistants, and support the teacher and help manage the class as a whole (Lyk and Lyk, 2015). Studies show an increase in learning gain by providing personalised hints (Leyzberg et al., 2014) or personalised problem selection (Gordon and Breazeal, 2015). Alternatively, the robots can also take the form of teachable agents, where the child learns by teaching the robot (Hood et al., 2015; Tanaka and Ghosh, 2011), or of a social partner or peer (Kanda et al., 2004). An example of the latter is where students used an "IROBI", a robot with an embedded touchscreen, to learn English as a foreign language at home (Han et al., 2005); the students with the robot showed greater concentration, interest, and achievement when compared to peers that had access to audio books or web-based learning only.

2.1.2 Socially assistive robots: components and challenges

Previous research has highlighted a number of key factors to consider when developing a *socially assistive robot*, they are: embodiment, personality, ability to understand the user, engagement, adaptation, and transfer of support to longer-term behavioural change (Tapus et al., 2007). Throughout this next section the key aspects identified and highlighted in the Figure 2.1 diagram are discussed. Some factors such as engagement are discussed across multiple aspects, e.g. embodiment and personalisation.

Socially assistive robots: modes of interaction

For a robot to be perceived as a social entity or offer support it needs to be able to interact with its users. Unfortunately, there are still some technical difficulties in respect to robotic communication via speech, this is due to the reliability of speech recognition software and difficulty in limiting the scope of the conversation (Blancas et al., 2015). However, robots can achieve good levels of social interaction with more limited non-verbal behaviours e.g. the minimal Keepon robot is able to convey attention and emotions with limited motion and simple beeps (Kozima et al., 2008).

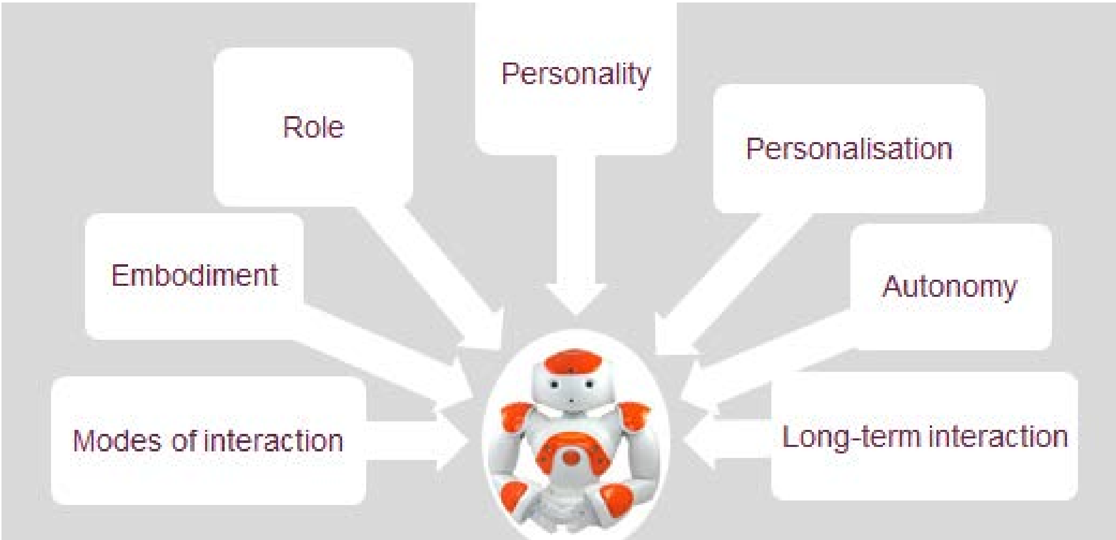

Figure 2.1: Aspects to be considered in the design of socially assistive robots

One of the key abilities of a physically present social robot is for the robot to be able to use gaze to enhance the interaction. Effective gazing from a robot in a cooperative task with a person has been shown to improve speed and accuracy of the person's actions in the task (Boucher et al., 2012). Likewise a robot can interpret human intent from the user's gaze (Sakita et al., 2004). It follows, that by using a model of social gaze, where the robot gazes at a task but occasionally gazes at the user, it is possible for the robot to engage the user (Fischer et al., 2015). It is also possible to have more advanced gaze behaviours, such as mutual gaze at the same location, and reciprocal gaze, where the robot gazes back at the user when the user looks at them. These abilities were implemented on a robot in the Emote project (Jones et al., 2015d). Likewise the robot could also adjust volume to match the user, as based on psychological theories, this type of contingent behaviour is important to build a social bond (Jones et al., 2015d).

When a social robot uses social contingent behaviour the results are extremely encouraging, for instance, the use of a socially contingent robot in a charity collection task, resulted in an increase in money collected when compared to a non-reactive robot (Wills et al., 2016).

Embodiment

One important factor of SAR is for there to be a physical embodiment as opposed to just a virtual embodiment. The robot's physical embodiment and appearance are fundamental for creating engagement and social bond (Tapus et al., 2007). While it is known that the embodiment plays a key role, it is not fully understood how this translates to measurable outcomes (Feil-Seifer and Matarić, 2005).

The physical presence of a robot can also influence the interaction; studies that compared robotic tutors against on-screen virtual agents showed a preference for robotic embodiment with reference to social presence (Kidd, 2003; Lee et al., 2006), enjoyment (Pereira et al., 2008; Kidd and Breazeal, 2004; Wainer et al., 2007), engagement (Kidd and Breazeal, 2004), trust (Hancock et al., 2011), performance (Hoffmann and Krämer, 2011), and learning gain (Leyzberg et al., 2012). The physical presence can also lead to a person showing more compliance to a robot's instructions and also giving more personal space compared to a virtual robot (Bainbridge et al., 2008). However, the physical embodiment does not appear to affect how a user would perceive the robots' displayed emotions (Bartneck et al., 2004).

Szafir (Szafir and Mutlu, 2012) argues that physical presence may increase the non-verbal immediacy of the social robot. Szafir highlights two possible mechanisms by which immediacy would then lead to benefits in the interaction, the *arousal-attention theory* where immediacy increases arousal leading to greater attention and engagement, or the *motivational theory* where immediacy would spark curiosity which would lead to an increase in inquiry and involvement (Szafir and Mutlu, 2012).

Personality and role

The personality of the robot is as important as the embodiment in creating a social bond and how the robot is perceived by the user (Tapus et al., 2007). One definition of personality is "the pattern of collective character, behavioural, temperamental, emotional and mental traits of an individual that have consistency over time and situations" (Tapus et al., 2007). This forms part of the definition of the role of the robot by Feil-Seifer "the impression it gives through its appearance and behaviour." (Feil-Seifer and Matarić, 2005). There are many roles that a *socially assistive robot* could play; e.g. a helper, assistant, companion, tutor, etc.

It can be argued that the personality of the robot must match the role that the robot plays to the user. If the robot has an overly social personality in a tutoring role then it may in fact harm the performance of the user (Kennedy et al., 2015). In fact the personality should also match the user's preferences for a robot personality which may lead to better task performance (Tapus et al., 2008).

Personalisation and adaptation

Personalisation is how the robot can employ a user model to understand and adapt to the user, e.g. adapting to the user's performance in an activity (Feil-Seifer and Matarić, 2005). By adapting to the user it is possible to gain higher levels of engagement and performance (Szafir and Mutlu, 2012). Engagement is an important aspect of SAR but an integrated approach is needed so that the robot can adapt to provide the necessary support (Gordon and Breazeal, 2015). Increasingly robots are starting to adapt in an empathic way to users i.e. taking account of the user's emotional states (Leite, 2013; Jones et al., 2015d).

One of the aims of SAR is for the support offered to transfer to longer-term behavioural change (Tapus et al., 2007). It is unlikely that one or two short-term interactions will lead to longer-term behaviour change so longer-term interactions must be supported. A review of studies that investigated longer-term interaction with robots (Leite et al., 2013) recommends that a robot should be able to display an awareness of and respond to the user's affective state and also adapt to the individual's preferences in order to build a good social interaction which is essential for longer-term support. Kanda's work shows that it is possible to build successful longer-term social relationships by using social behaviours, adapting to each child, and confiding personal matters to children (Kanda et al., 2007).

2.1.3 Summary

It is clear from the above research that SAR has the ability to support, motivate, and develop skills and knowledge in a large number of domains. There is increasing interest in bringing the capabilities of *socially assistive robots* particularly into educational domains.

2.2 Social robots in education: state of the art

In this section the application of SAR to support learners in an educational scenario is discussed in more detail. As discussed above, SAR projects can bring a wealth of benefits to the domain in which they operate. A robotic embodiment is key to this research project, as the physical presence, behaviour, and social interaction of *socially assistive robots* can engage and motivate users to develop desirable skills and abilities. It follows that robots can be used to address the problem of offering children enough one-to-one support (Scassellati, 2016) and also offer engaging longer-term support or guidance (Leite et al., 2013).

While this thesis does not seek to compare *socially assistive robots* to human tutors there may be some benefits of robotic tutors over human tutors. For instance, robots may be more patient and allow the children to work at their own pace, whilst also being available at any time to the users.

Research that has compared robot intervention to human intervention (Huskens et al., 2013) found that both interventions were successful, but suggests that robots need to adapt to the users' individual preferences and abilities. Some research has also shown that while students will follow instructions from a robot to successfully complete a task (Serholt et al., 2014b), the students did not seek help from the robot as much as from a human tutor.

2.2.1 Examples of robotic tutors

A number of studies are highlighted below to provide an overview of the field of *social robotic tutors*. Robots can play the role of a tutor by assisting with hints (Leyzberg et al., 2012) or lessons (Kennedy et al., 2015). Tutors have been used in different educational subjects and are increasingly showing more sophisticated adaptation to the learner and increased social-cognitive awareness (Belpaeme et al., 2015).

Figure 2.2: NAO robot as used on the EMOTE project

Examples of projects that are using theories of social-cognitive awareness are the EMOTE project[1], which has explored the use of an empathic robotic tutor to respond to the affective states of the learner; and the L2TOR project[2], which uses a robotic tutor to assist with language learning with an aim of adapting to nonverbal signals (Belpaeme et al., 2015).

As discussed in the overview of social robots in education in section 2.1.1, it is possible to have robots in an education setting that do not teach, such as teachable agents or companion robots. The CoWriter project[3] uses a teachable robot so

[1]http://emote-project.eu/
[2]http://www.l2tor.eu/
[3]http://chili.epfl.ch/cowriter

children can acquire handwriting skills while teaching a robot to write. The CRR Project[1] is exploring using a care-receiving robot to help students learn language through a *learning by teaching* scenario (Tanaka and Matsuzoe, 2012).

2.2.2 Social interactions with robotic tutors

There are limitations with the interaction modalities of social robots at present as described in section 2.1.2, which presents challenges as regards to obtaining a meaningful social interaction. To overcome these limitations, techniques such as Wizard of Oz (WoZ) studies, where a robot is controlled by a human "wizard" (Dahlbäck et al., 1993), are used to investigate how learners interact with a robot. As detailed below, it is still possible to achieve an autonomous social interaction with a robot in educational context with careful design. One example is a touchscreen "Sandtray" (Baxter et al., 2012), this is a touchscreen that both the user and robot can interact with that allows both parties' environmental manipulation. In this scenario it is also possible for the robotic system to know what the learner is doing and respond in an appropriate manner whilst effectively avoiding the technical limitations of speech recognition as discussed previously.

2.2.3 Personalisation

Within education personalised tutoring is very important, students that are tutored one to one perform significantly better than when taught in a group (Bloom, 1984). One of the motivating factors behind the use of robots in education is to create a robot that can provide one to one support (Ramachandran and Scassellati, 2014; Kennedy et al., 2015). Effective one to one tutoring requires the tutor to assess students' individual differences and align their support to best suit an individual student's needs (Leyzberg et al., 2014; Gordon and Breazeal, 2015). As such there

[1] http://fumihide-tanaka.org/lab/en/research.html

is increasing interest in how HRI can personalise or adapt to the learner. This personalisation can take many forms; highlighted below are some of the ways that this is achieved:

- **Task performance**. A robotic tutor that personalises hints and tips based on a student's puzzle solving skills can lead to a more successful interaction with reduced problem solving time and a more motivated learner (Leyzberg et al., 2014). Prompts personalised to a specific level of detail based on the ability and performance of the learner can be more effective and less frustrating (Greczek et al., 2014).

- **Engagement levels.** Robots can also personalise an interaction based on a learner's engagement e.g. recall levels can be increased by adapting robotic behaviours to engagement as measured with an EEG headset (Szafir and Mutlu, 2012). Given that the use of an EEG headset is rather unnatural there is work underway to measure and adapt to engagement using cameras, microphones, and Kinect sensors (Ramachandran and Scassellati, 2014; Deshmukh et al., 2015a).

- **Affective states.** There is also an increasing amount of work that is investigating how personalisation can be used to adapt to the affective states of the learner (Ramachandran and Scassellati, 2015; Jones et al., 2015d; Leite, 2013).

- **Learning styles.** It is proposed that by adapting to the learning style of a child a robot could increase accessibility of the learning scenario (Clabaugh et al., 2015).

- **Child's cognitive development needs.** There is also interest in adapting the robot based on a child's cognitive development, e.g. a robot offering support as a tutor but then moving to the role of a peer to expand the user's zone of proximal development (Charisi et al., 2015).

There is an increased interest in developing models for the use in personalisation by using machine learning techniques taking into account multi-modal factors e.g. where a robotic tutor adapts its approach by learning the best strategies for each user by updating estimates of the outcome of a strategy based on measuring the user's affective state after each use of that strategy (Leite et al., 2011) .

2.2.4 Socially supportive behaviour and impact on motivation and engagement

One of the main benefits of the robotic tutor is that it can motivate students to engage in the learning scenario (Kennedy et al., 2014; Leyzberg et al., 2014; Kanda et al., 2007). One factor in motivation of the student lies with the socially supportive behaviours of the robot; using an expressive robot can lead to more efficient learning (Saerbeck and Schut, 2010). Social behaviours must however be implemented in an appropriate manner for the role of the robot; in one study a robotic tutor with social behaviours led to less learning than a *social robotic tutor* (Kennedy et al., 2015). This may be due to the robot distracting from the task (Kennedy et al., 2015); it is important to use the robot to balance engagement between the task and the robot itself (Corrigan et al., 2013).

2.2.5 Longer-term studies

In longer-term interaction studies with robots in education there are good levels of social acceptance and engagement (Leite et al., 2013; Tanaka et al., 2007), which suggests that in the longer-term these robots will be able to support learning gain. To be effective in longer-term interactions the robot should be able to display an awareness of, and respond to, the user's affective state and also adapt to the individual's preferences in order to build and maintain a good social interaction (Leite et al., 2013). Another way to build a bond between the robot and learner is to use memory to recall past activities (Leite, 2013).

2.2.6 Viewing social robotic tutors through a socio-constructive learning lens

All of the projects using a social robot as a tutor or peer could be argued to have as a basis the socio-constructivist approach to learning. Socio-constructivist theory is concerned with the cognitive development of the individual from social interaction (Tongchai, 2008). It is believed that *socially assistive robots* can support the best practises of socio-constructivist learning theories (Clabaugh et al., 2015), such as playful interaction (Short et al., 2014). Some more open-ended learning scenarios allow the learner more control and exploration, in line with Papert's constructionist theory (Papert, 1980), which involves learning through self-directed and playful exploration of the learning scenario (Dautenhahn and Werry, 2004). Other approaches are linked to Vygotsky's Zone of Proximal Development(ZPD) theory, where the social robot can adjust the difficulty of the task either directly, or by offering support at an appropriate level for the learner to learn from it (Short et al., 2014; Gordon and Breazeal, 2015).

2.2.7 Summary

Socially assistive robots robots have the ability to support learners by motivating and engaging learners in the learning scenario. They are able to use their social affordances to help learners build knowledge and skills. However, social robots have not yet been used to support SRL skills.

2.3 Self-regulated learning

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 (Zimmerman, 2008). SRL skills are seen as relevant and essential for the 21st Century (Dembo and Eaton, 2000; Shute, 2011; Roll et al., 2014b). The use of SRL strategies is significantly correlated with measures of academic performance (Zimmerman, 2008). However, it may not be easy for students to be meta-cognitively or motivationally active during the learning process (Azevedo et al., 2011), and as a consequence students will not use or develop SRL skills. If students lack SRL skills they will struggle to learn in the future, particularly if the learning task requires independent learning, is open-ended, or not well defined.

2.3.1 Models and key components of SRL

There are a number of models of SRL, e.g. the work by Boekaerts (Boekaerts, 1997), Pintrich (Pintrich, 1999), Winne (Winne and Perry, 2000) and Zimmerman (Zimmerman, 2008). These models share similar phases of SRL: the preparation, performance, and appraisal phases (Puustinen and Pulkkinen, 2001). All models agree that a key element of SRL is the appraisal phase where a learner reflects upon and self-assesses their own performance. Social constructivist theory views reflection and discussion as a vital mechanism in the construction of knowledge (Reingold et al., 2008). Figure 2.3 shows Zimmerman's cyclical SRL model.

Pintrich (Pintrich, 1999) highlights the importance of mastery goals, positive self-efficacy and task value in motivating the use of developing SRL skills. Pintrich and Zimmerman's theories are based in social cognitive theory (Puustinen and Pulkkinen, 2001), espoused by researchers such as Bandura (Bandura, 1991). This indicates that self-regulation does not happen in isolation but within a social interaction. It may be that the social interaction helps to motivate the learner to engage

Figure 2.3: Zimmerman's cyclical SRL model: phases and sub-processes of self-regulated learning

in these SRL skills.

2.3.2 Scaffolding SRL

Vygotsky's (Vygotsky, 1978) work suggests that learners can be guided by a more capable peer to solve a problem or carry out a task that is beyond them (Azevedo et al., 2011). Scaffolding is the process of providing assistance as it is needed, then fading or removing this support when the learner no longer needs the support. Boekaerts (Boekaerts, 1997) suggests that students that are weak in SRL skills need external regulation to adjust their SRL behaviours (Lin et al., 2015). This is in line with social constructivist theory.

Scaffolding can take the form of structuring activities to allow a student self-assessment or self-explanation (Chi et al., 1989); provide hints and feedback on performance (Azevedo et al., 2011) (otherwise known as formative assessment (Shute, 2008)); or motivate a student to continue in a task (Merrill et al., 1995). Appropriate support from a tutor can support students to experience learning through reflective and meta-cognitive processes (Reingold et al., 2008). However, there is a risk that a learner can become dependant upon a tutor for the regulation (Azevedo et al., 2011), so care must be taken to ensure that there are opportunities for the learner to regulate their own learning. Meyer (Meyer and Turner, 2002) gives examples of how the autonomy of the learner can be supported and how the responsibility for use of SRL skills can be transferred to students. As with any type of tutoring, adaptive or personalised scaffolding is more effective than when fixed prompts, or no scaffolding is offered (Azevedo et al., 2004).

2.3.3 Scaffolding SRL in ITS

An ITS is a computer system that aims to provide personalised support to a learner (Graesser et al., 2012; Bull and Kay, 2013). To achieve this the system has models of the domain/subject, the learner, and a pedagogical model; these components allow personalisation to the learner (Bull and Kay, 2013; Sottilare et al., 2014). There is increased interest in moving from ITS that supports domain learning to ITS that supports meta-cognition and SRL (Roll et al., 2014b; Graesser et al., 1999; Koedinger et al., 2009). ITS that supports meta-cognition can increase meta-cognition and improve learning outcomes (Koedinger et al., 2009). Roll (Roll et al., 2014b) describes four main ways that SRL can be supported in ITS:

- **Demonstration**. This approach involves an agent (tutor or peer) demonstrating good SRL behaviours. A learning planning application that shows the learning goals and plans of peers who have good SRL skills can lead to adoption of good SRL skills by learners that observe them (Lin et al., 2015). Alternatively, a learner can be prompted to reflect on their learning process by teaching a teachable agent such as Betty's Brain (Wagster et al., 2007a; Biswas et al., 2010). A learner can observe a teachable agent's SRL strategies, the learner and the agent can make comments about how effective the SRL strategies are in the learning scenario, and the learner can then use these insights to improve their own behaviour (Wagster et al., 2007a).
- **SRL prompts**. This approach is where the learner is prompted to use SRL strategies in the learning scenario. The SRL scaffolding is considered static as it is not dependent on the state of the student's meta-cognition (Koedinger et al., 2009). Fixed prompts such as pre-identifying sub goals in a task can be effective in human studies (Azevedo et al., 2004). The MIRA learning system (Gama, 2004) prompts the learner to reflect upon their self-assessment accuracy. Prompts for periodic self-assessment can lead to increases in learning outcomes and self-assessment accuracy (Long and Aleven, 2013a). There are also a number of systems that prompt learners to self-explain (a.W.M.M. Aleven and Koedinger, 2002; Conati and VanLehn, 2000). While in the process of self-explanation it is thought that students reflect more upon the activity

and the information that they require to provide an answer (a.W.M.M. Aleven and Koedinger, 2002). Self-explanation helps learning by having the students identify gaps in their knowledge. By verbalising and explaining themselves the student is required to think about the problem in a different way, which may lead them to learn in more depth (a.W.M.M. Aleven and Koedinger, 2002).

- **Adaptive SRL feedback**. This approach is where feedback is given on the SRL skills demonstrated by the learner. The principle behind this is the same as for any formative feedback that can help to improve any skill or knowledge (Shute, 2008). This type of adaptive support can then enable the students to use the SRL skills to learn more effectively in the learning task (Azevedo et al., 2011). An example is where real-time monitoring and personalised scaffolding of help seeking behaviour can improve a student's help seeking behaviour in the system (Roll et al., 2011). Feedback on self-explanation skills can improve the quality of self-explanation (a.W.M.M. Aleven and Koedinger, 2002).

- **Cognitive tools**. This approach provides cognitive tools in the environment that help students offload cognitive processes associated with the task (Roll et al., 2014b; Jonassen, 1992). An example of a cognitive tool is a tool that can help students make hypotheses and test them, e.g. the Crystal Island learning environment (Shores et al., 2011). Another example is an electronic notebook CoNoteS2 (Hadwin and Winne, 2001) that can help students understand tasks, create personal goals and plans, and review and track learning. It is thought that the use of these tools engages the learner in the task at hand and makes them more aware of the effectiveness of using these types of reflective thought processes (Jonassen, 1992).

Much of the SRL support or regulation described above is external in nature i.e. where the learner does not initiate the SRL behaviour. With such external regulation the learner may not internalise the SRL skills. For a learner to gain more autonomy in using SRL skills an ITS tries to reduce the scaffolding or support for those skills (Roll et al., 2014b). Kitsantas (Kitsantas, 2013) gives a road-map for how the shift from external to self-regulation might be achieved, first by demonstrating the SRL skills, then by allowing the student to practice with feedback, then by allowing practice through limited supervision, and then finally allowing students to pursue fully self-regulated learning with a focus on outcomes. The aim is to move away from external regulation where the student is told exactly what to do, to co-regulation where the system and the students negotiate a way forward, to finally the student being purely self-regulated. A key element in SRL scaffolding approaches is to prompt reflection and highlight to a learner the gaps in their knowledge or skills. Roll suggests that an OLM is one method to prompt reflection to support co-regulation between the system and a user (Roll et al., 2014b).

2.3.4 OLM background

One of the tools used in an ITS to support SRL is an OLM. OLM externalise the model that the system has of the learner in a way that is interpretable by the learner (Bull and Kay, 2010). OLM frequently take the form of a series of skill meters (Bull et al., 2010; Long and Aleven, 2013b; Mitrovic, 2007); an example from SQL Tutor (Mitrovic, 2007) is provided in Figure 2.4. An OLM can support SRL by promoting reflection to raise awareness of understanding or developing skills, which in turn can help planning and decision-making (Bull and Kay, 2013).

Self-assessment is the ability for a learner to accurately assess their knowledge and skills in relation to their actual performance; this ability is very important in learning (Tobias and Everson, 2002). OLM, when used to support reflective self-assessment activities, can have a positive effect on self-assessment and on learning outcomes (Kerly et al., 2008; Mitrovic and Martin, 2002; Long and Aleven, 2013b).

An OLM can further support SRL when the learner is able to control their

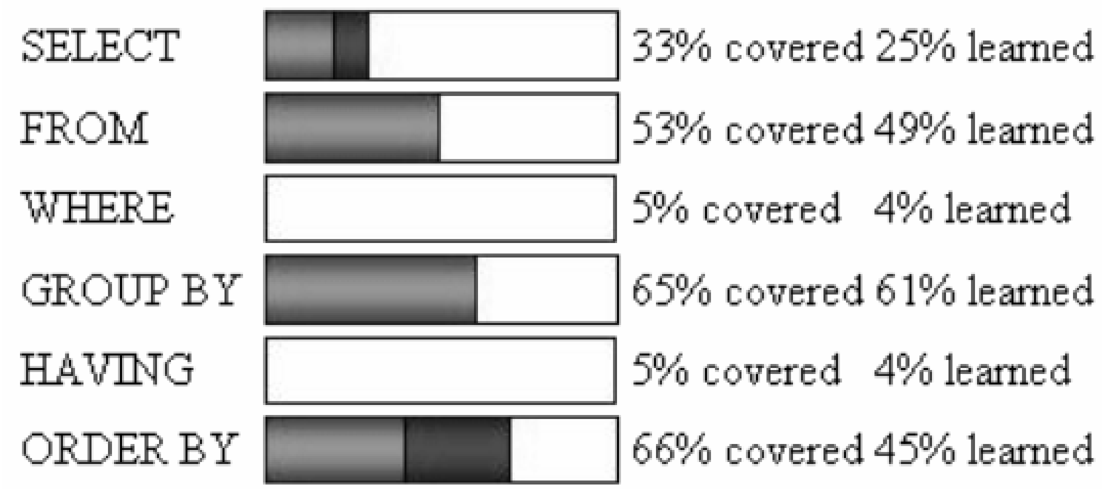

Figure 2.4: OLM skill meters from SQL tutor, Mitrovic 2007

own learning in the learning scenario, e.g. undergraduate students were able to use an OLM to identify misconceptions and better allocate their effort to meet their learning needs (Bull et al., 2010). Students can use an OLM to select the most appropriate problems that may allow more effective learning (Mitrovic, 2007).

The above results are achieved with simple inspectable OLM which present the learner model in an easily accessible way. More advanced OLM allow the learner to negotiate with the OLM and arrive at an agreement (Kerly, 2009). The process of negotiating the learner model can cause learners to become more engaged, reflect more, and help the learner develop better self-assessment skills (Kerly, 2009).

KERMIT

KERMIT (Knowledge-based Entity Relationship Modelling Intelligent Tutor) and its extension e-KERMIT is an ITS designed to support the learning of Entity-Relationship knowledge (Hartley and Mitrovic, 2002). It contains an OLM that continuously displays a high-level summary of the student's progress (Figure 2.5), with more detailed information available on request (Figure 2.6) (Mitrovic, 2007). The use of the OLM in KERMIT has a positive effect on learning and students' meta-cognitive skills (Mitrovic, 2007). In addition to significantly better performance over peers without access to the OLM there also appears to be greater motivation to spend time problem solving. In KERMIT there is a preference for a more simple representation of the OLM as a set of skill meters over concept maps (Duan et al., 2010).

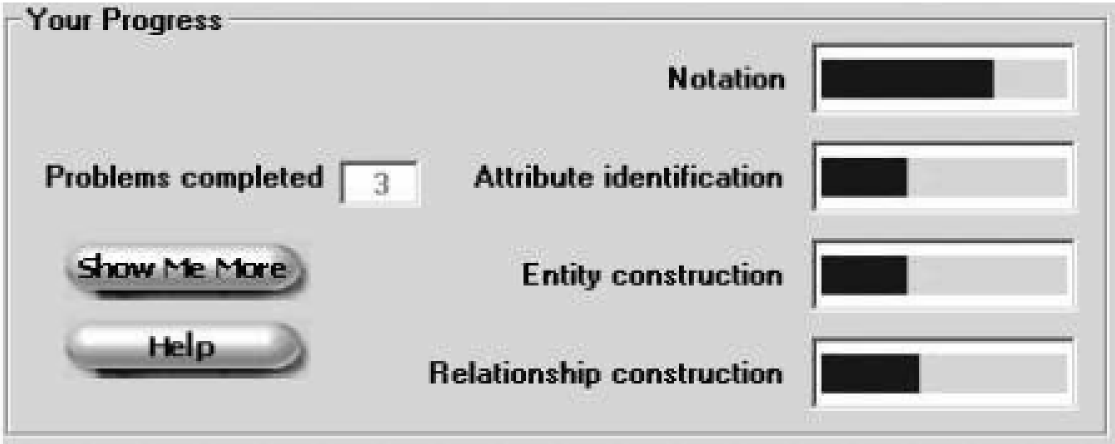

Figure 2.5: High-level summary in OLM from e-KERMIT, Mitrovic 2007

2.3.5 Summary

From the above review of theory and research, it is clear that a learner must be able to reflect, self-assess, identify gaps in knowledge, and have control in the learning scenario in order to engage, practice, and effectively develop SRL skills. It is also beneficial to motivate students to engage these skills. Social interaction can play a large part in motivating students to do this; in addition, prompts to reflect, self-assess, help set goals, and positive feedback (to increase self-belief), and formative feedback can also help improve SRL skills.

OLM can be a way to highlight gaps in knowledge and skills that the learner can use as a basis for reflection, self-assessment and planning. By combining an OLM with a learning scenario that allows the learner a level of control, the learner has an opportunity to move from co-regulation of SRL to full SRL (Roll et al., 2014b).

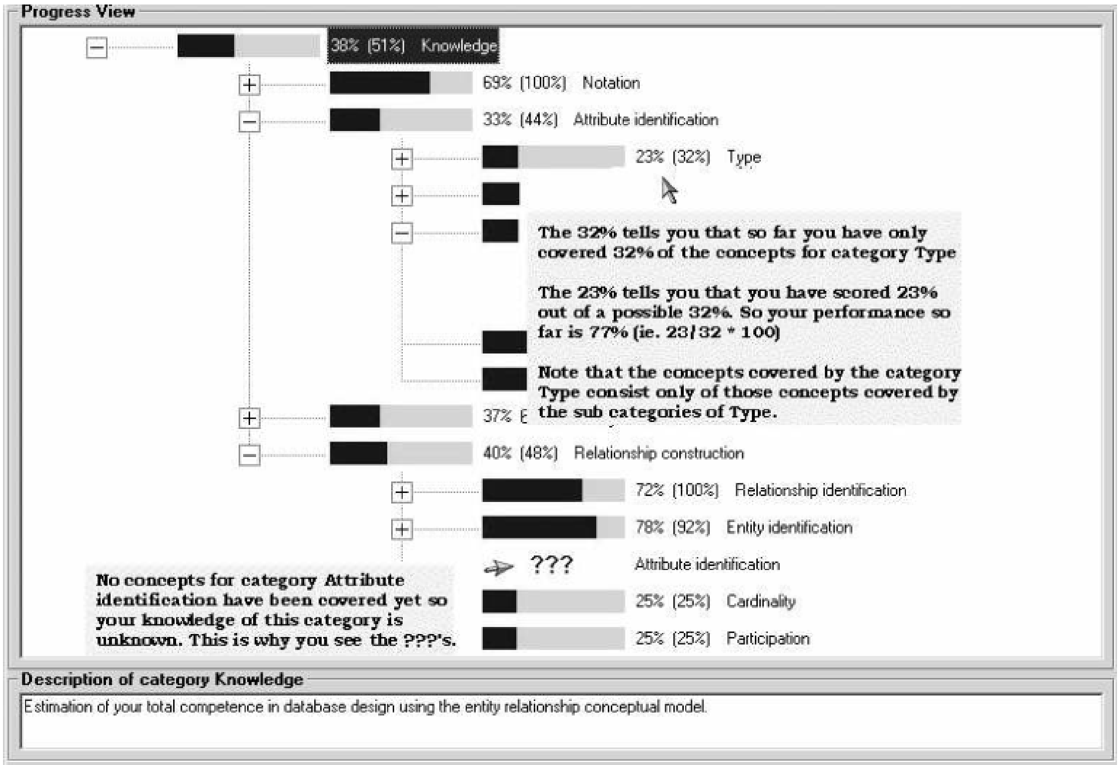

Figure 2.6: Detailed visualisation of the OLM from e-KERMIT, Mitrovic 2007

2.4 Conclusions

Social robots can bring many benefits to an education environment through increased social interaction. The improvement in the learning process can be explained by social constructivist theories. From ITS and HHI studies it is observed that personalisation is an important part of building an effective relationship and learning scenario. Within HRI it is observed that the physical embodiment of a robotic tutor that adapts to a learner can lead to a greater feeling of immediacy and greater engagement between a learner, the robot and the activity.

However, social robots have not been used to support SRL skills. SRL skills are important in learning and social interaction is important for developing these skills. One key aspect of SRL is reflection; OLM can form an important part of feedback to enable reflection and SRL. OLM can also be the basis for co-regulation of SRL.

This thesis proposes to use a social robot to engage and motivate a learner to use SRL processes in a learning scenario. Learners will have access to an OLM so that they can use the personalised information provided to reflect, which is a key process of SRL and the foundation of good SRL skills. The robotic tutor should use the OLM as a basis to scaffold SRL, by moving from demonstrating or prompting good SRL behaviours, to supporting the learner so that they can use the OLM for co-regulation of learning, through to the learner being able to use SRL skills with no support at all.

CHAPTER 3

USER-CENTERED DESIGN

This chapter discusses the design methodology that was used to elicit requirements and create specifications to develop a social robotic tutor to scaffold SRL skills. An iterative UCD approach was followed for the development of the learning scenario and the role of the robotic tutor. This approach fits well with the aim of not developing a robotic tutor to replace a human teacher, but rather to explore how a robot's capabilities can be developed to facilitate children's SRL, with a view to designing new learning scenarios that may support the teachers in a classroom environment. The robot is designed to work in the user's environment and interact in socially appropriate ways. The approach is similar to one used in developing socially supportive robots (Dautenhahn and Werry, 2004).

The chapter begins with a definition of UCD (section 3.1) and how this has been applied to adaptive systems in HCI and HRI. Followed by an overview of the UCD process (section 3.2) which describes the design goals, research questions, and iterative process. This is followed by a section detailing some methodological consideration (section 3.3) including recruitment of participants, and details of the experimental setup. The remainder of the chapter describes the UCD studies in detail. It is hoped that this can form a process map for other researchers to follow.

3.1 Definition of UCD

User-centered Design (UCD) can be a broad term to mean a design process in which end-users influence how a system is designed (Abras et al., 2004). In this research a more specific definition is followed where UCD is defined as a framework made up of the following phases: understanding the context of use, elicit users' requirements, develop a system against the requirements, evaluate the system against the requirements, usability, and user experience. The result being that users should be included in all phases of system development. The key principle is to adapt the system to the context and the user, rather than force the user to adapt to the system.

UCD is an alternative to a technology-driven or system-driven approach which can focus primarily of the development of technological or system improvements. Within the field of HRI a technology-driven approach is often adopted by HRI researchers (Kim et al., 2011). This can also be the case in the field of ITS, even when developing systems that should adapt to the users, those users may not be consulted or involved until the system's evaluation (Santos and Boticario, 2015).

UCD can sometimes even extend to participatory design where the users co-design the system (Abras et al., 2004). The benefits of UCD include a greater sense of ownership of the system, greater satisfaction with the product, and a greater ease of use of the system (Abras et al., 2004). When applying UCD to HRI and focusing on the study of a user's interaction with the robot, a robot can be developed that is better able to assist the user in achieving their goals, leading to a higher quality of user experience (Kim et al., 2011).

UCD for *Human Computer Interaction* (HCI) has been formalised as ISO 9241–210[1], human-centered design for interactive systems:
"ISO 9241–210:2010 provides requirements and recommendations for human-centered design principles and activities throughout the life cycle of computer-based interactive systems. It is intended to be used by those managing design processes, and is

[1]https://www.iso.org/standard/52075.html

concerned with ways in which both hardware and software components of interactive systems can enhance human–system interaction."

The standard describes 6 key principles to ensure the design is user-centered:

The design is based upon an explicit understanding of users, tasks and environments. This can be achieved by carrying out background interviews and questionnaires, focus groups, and on-site observations (Abras et al., 2004).

Users are involved throughout design and development. This means that the user involvement does not stop after the initial interviews. This continuity can be achieved with participatory design techniques, or by having users evaluate the design and implementation at various stages of development.

The design is driven and refined by user-centered evaluation. This can be achieved by evaluating prototypes with users as the design and development progresses, as recommended in HRI research (Bartneck and Hu, 2004; Kim et al., 2011). It is important to test the usability of the system at various stages not just at the very end of the development process when it is too late to make further changes.

The process is iterative. An iterative approach increases the amount of input that can be provided by the users. It can be difficult for users to explain in detail their requirements based on abstract descriptions of a system. An iterative approach enables users to overcome this difficulty by providing input on something concrete.

The design addresses the whole user experience. This means that the design does not just address the ease of use of the system, but takes into account other factors in the user experience. For example, this will include learning gain in an ITS or perception of the robot in HRI.

The design team includes multidisciplinary skills and perspectives. This principle aims to ensure that different perspectives are taken into account in the design process.

The standard also provides an overall structure for UCD, and includes a checklist of activities required to adhere to the standard, in the following phases: planning, specification of context of use, specification of user and organisational requirements, production and testing of design solutions, and evaluation of designs against user requirements (Bevan and Curson, 1999). Previous research (Santos and Boticario, 2015) has adopted and merged the ISO standard with other methodologies that focused on developing and evaluating systems for interactive adaptive systems (Paramythis et al., 2010; Van Rosmalen et al., 2004; Santos, 2009). The resulting methodology is called TORMES and it recommends that UCD activities defined by ISO 9241–210 are used in three iterations: proof of concept, elicitation of educational recommendations, and delivery of recommendations (Santos and Boticario, 2015). A summary of the UCD phases and activities specified by ISO 9241–210 and TORMES is presented below:

Understanding and specifying the context of use: Identifying the primary users of the system, what they will use it for, and under what conditions they will use it. This includes activities such as interviews and focus groups.

Specifying the user requirements: Identifying requirements and user goals that should be met for the system to be successful. This phase should try to consider a variety of viewpoints. This can take the form of background interviews and questionnaires (Abras et al., 2004). This can also take the form of role playing, walk-throughs, and simulations (Abras et al., 2004). If this is not the first iteration then evaluation an interpretation of data collected in previous iterations can also be used to specify user requirements. This could be achieved with data mining techniques (Paramythis et al., 2010).

Producing design solutions: This is where the system is designed to meet user requirements. This can be an initial rough concept in early iterations to the full system design and implementation in later iterations. This phase is where prototypes are developed as recommended in HRI research (Bartneck and Hu, 2004; Kim et al., 2011). TORMES (Santos and Boticario, 2015) recommends that this phase is split into a modelling phase where the design is validated by users, and a publication phase where the implementation is created and presented. This can take the form of focus group and card sorting (Santos and Boticario, 2015).

Evaluating the design: This is where the system is evaluated against the requirements. Evaluation of the system is a crucial step that provides formative feedback that can be turned into further requirements in the next iteration of system design. This often takes the form of usability testing where data is collected that is related to measurable usability criteria (Abras et al., 2004). This phase is used to improve the system's usability, involve real users in the evaluation, give the users real tasks to accomplish, and enable the researcher to observe and record the actions of the users (Abras et al., 2004). TORMES (Santos and Boticario, 2015) recommends splitting this into a usage phase, where users interact with the system, and a feedback phase where the interaction is analysed and feedback created. TORMES (Santos and Boticario, 2015) also recommends evaluation of adaptive systems using a "layered" methodology, which involves formative evaluation of different layers of the adaptive system. In earlier iterations of system development, "layered" evaluation evaluates the quality of input data, the validity of inferences, and accuracy of models developed (Paramythis et al., 2010). In later interactions the "layered" evaluation evaluates the appropriateness of adaptation and whether the implementation of the adaptation decisions made is optimal.

3.2 UCD Approach

This section details the UCD approach followed in this research. A UCD approach is used rather than a technology-driven approach. Users were involved in the development of the robot with the aim of making the robot more socially acceptable (Šabanović, 2010; Belpaeme et al., 2013; Jones et al., 2015d; Kim et al., 2011) and effective in supporting SRL skills.

As has been discussed previously the formation of a good social relationship between learner and teacher is paramount in facilitating a good overall learning experience. It is believed that one way to make tutoring systems more effective is to include a robot that will no longer just be intelligent, usable, and interactive, but will also be able to establish and maintain a certain level of social connection (Leite et al., 2013). The ability to form this relationship may come naturally to an attentive teacher, however it is proposed that by using UCD tools and analyses of HHI a robotic tutor may also be endowed with this ability. In this research there are two types of end users: the teachers, whose classrooms the robotic tutor will operate in; and the learners, who the robotic tutor aims to support. In education there is a need to balance the teachers' educational goals as well as learners' preferences (Santos and Boticario, 2015).

The UCD approach is guided by the design goals described in subsection 3.2.1. These design goals can help ensure that the competencies of the robotic tutor are implemented in an appropriate and believable manner, have real world application in the complex school environment, and meet the needs of both learners and teachers (Jones et al., 2015d). Based on these design goals an iterative UCD process was performed to investigate how to enable a robot to display key social and SRL scaffolding abilities as detailed in subsection 3.2.2.

3.2.1 Design goals

To develop a robot that is accepted into a school context and that is effective in supporting the development of SRL skills, the following design goals (DG) should be met:

- **DG 1.** Involve end users (teachers and learners) in the design of the robot and the learning scenario. When technology is introduced into the classroom it becomes part of a complex system of social and pedagogical interactions, involving both teachers and learners (Russell and Schneiderheinze, 2005), therefore it is pertinent to investigate the perspective of the potential users as well as the social and contextual structures inherent in the environment (Koedinger et al., 2009). This goal takes into account key principles ISO 9241–210:2010: "the design is based upon an explicit understanding of users, tasks and environments", and "users are involved throughout design and development" with users involved in the design from an early stage, from setting the context of the system and requirements all the way through to the evaluation of the system.

- **DG 2.** Investigate how the capabilities of the robot are perceived by the users. Some of the capabilities of the robot are based on HHI and literature, HRIs are not routinely based on HHI due to the differences in how users perceive robots and humans (Dautenhahn, 2007), the introduction of these capabilities must be evaluated. It is also a recommendation from "layered" methodology to investigate the effectiveness of different aspects of adaption to a user (Paramythis et al., 2010). It is also good UCD in HRI practice to prototype and test capabilities in the robot iteratively and in situ (Sabanovic et al., 2014; Bartneck and Hu, 2004) with a focus on the interaction (Kim et al., 2011). This goal takes into account key principles ISO 9241–210:2010: "the design is driven and refined by user-centered evaluation" and "the design addresses the whole user experience" as this goal leads to studies where many aspects of the user's interactions and experience are observed and then turned into requirements for further development.

- **DG 3.** Identify personalised pedagogical strategies from human interactions. Successful personalised tutoring has to attempt to identify pedagogical strategies that are most effective in establishing, strengthening, and sustaining social bonds and supporting SRL behaviour. HRI studies that are based on human interactions can be quite successful, e.g. adopting human gaze behaviour to increase engagement with the robot (Sidner et al., 2005). This goal takes into account key principles ISO 9241–210:2010: "the design is driven and refined by user-centered evaluation", and "the design addresses the whole user experience", "the design team includes multidisciplinary skills and perspectives" as this goal leads to studies including teachers and learners where many aspects of the user's interactions and experience are observed and then turned into requirements for further development.

- **DG 4.** Tie the robot capabilities to well supported pedagogical theories. The development of personalised learning strategies should specifically target those concepts that have been shown to be empirically well supported and enable the robot to adapt to individual differences. Personalised learning approaches should, in particular, aim to identify cues that teachers use to personalise their teaching styles. This goal takes into account key principles ISO 9241–210:2010: "the design team includes multidisciplinary skills and perspectives" as it leads to the inclusion of requirements and specification from pedagogical experts.

In the next section the iterative approach of the design process is described in line with the design guidelines detailed above. The process is iterative which fulfils the final guideline of ISO 9241–210:2010 ("The process is iterative").

3.2.2 Design process and design activities

This section describes the iterative design process, including the phases used in each iteration, the research questions and goals of each iteration, and the methods and UCD activities in each iteration. Four of iterations of the UCD phases and UCD activities were performed as part of the UCD process. Each design activity/study built upon the results from the previous activity/study. Each iteration contained the same phases and slightly different UCD activities based on the level of maturity of the system and the research questions. This type of iterative approach that repeats the same phases is similar to the spiral development process (Boehm and Hansen, 2000).

At a high level, the iterative design follows the process shown in Figure 3.1; first the planning phase, then the development phase, and finally the evaluation phase for the next iteration. Table 3.1, Table 3.2, and Table 3.3 show how this process is followed in detail and highlight the key research goals and results or contributions.

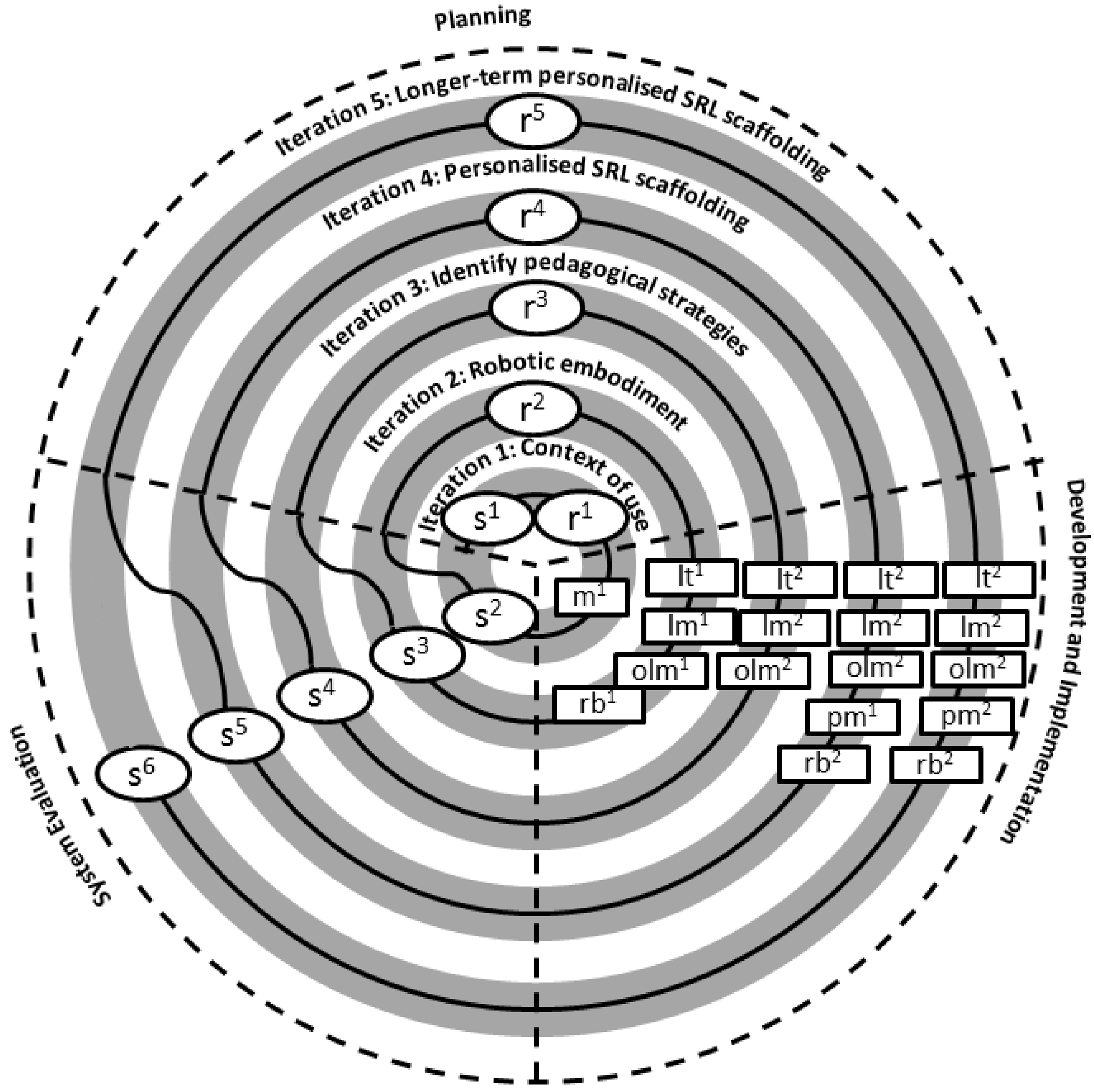

Figure 3.1: Iterative UCD process to ensure competencies of the robotic tutor are implemented in an appropriate and believable manner, have real world application in the complex school environment, and meet the needs of both learners and teachers. Superscript shows the version. Abbreviations used: s: study; r: requirements; m: mock-up; lt: learning task; lm: learner model; OLM: open learner model; rb: robot implementation

In this research the end users are both the teachers whose classrooms the robotic tutor will operate in and the learners that the robotic tutor aims to support. As mentioned above, a participatory design approach is not followed as this would have required more resources, time, and availability of the users. Additionally the learners would not likely posses the design skills required to be included in participatory design. Although this means there is less learner involvement in the development and implementation phase, however, there is a high level of involvement in the planning and system evaluation phases. There is a risk that if the main source of user requirements is from evaluation, then the input is based on reaction rather than from the users' initiation, arguably resulting in the input from users being provided too late in the development process to have much benefit (Scaife et al., 1997). This also breaks a recommendation from spiral development to include users in system construction (Boehm and Hansen, 2000). However, an informant design approach is followed to improve the efficiency of input from both teachers and learners (Scaife et al., 1997). In addition, further mitigation is achieved by letting teachers define the initial context and learning goals for the learners (Scaife et al., 1997) and by performing many iterations of the design process with low and higher tech prototypes (as recommended by Scaife (Scaife et al., 1997)). It can also be difficult for teachers to articulate how the system could help them (Scaife et al., 1997), however a successful solution to this involved gathering requirements by observing teachers in HHI. The learning task design is based on existing educational material as discussed in section 4.2. In addition, other development and implementation is based on best practice from literature as described in section 5.1.

Each iteration had the following UCD phases:

- **Planning**. This phase includes 'understanding and specifying the context of use' and 'specifying the user requirements' from ISO 9241–210. As this is a research project this is also where the research goals and questions are identified. To support this phase the activities carried out included interviews with teachers, reviewing literature, and analysing previous formative evaluations of the system to specify requirements. This is the main phase in which teachers had input into the direction of development. The planning takes into account "layered" evaluation (Paramythis et al., 2010) for the adaptive elements of the system. The aim is to isolate and evaluate pieces of adaptation. In early iterations the planning ensures that the building blocks of the modelling and adaptation are evaluated. In later iterations the planning ensures that the appropriateness and implementation of adaptation is evaluated.

- **Development and Implementation**. This phase includes 'producing design solutions' from ISO 9241–210. In addition to the design of system components to meet the user requirements this also includes the design of studies to answer research questions. Following a review of the study and system design the necessary steps to implement the study and system components are carried out. End users were not directly involved in this phase. With more resources it may be possible to have the design reviewed by users as is suggested in the TORMES (Santos and Boticario, 2015) and spiral (Boehm and Hansen, 2000) methodology. In earlier iterations this phase would lead to the development of prototypes. In later iterations this phase would lead to full system development with an autonomous robotic tutor.

- **System Evaluation**. This phase includes 'evaluating the design' from ISO 9241–210. In this phase studies are run with end users and then evaluated to create a formative evaluation for input into future iterations. Some of the practicalities of running these studies are described later in this chapter in section 3.3. The results have implications for the definition of the research questions and goals of the next iteration. This is in line with the TORMES (Santos and Boticario, 2015) methodology which includes a usage phase where the users use the system or prototype in the study, followed by a feedback phase where the interactions with the system or prototype in the study are analysed and feedback is generated for further system development. In this phase careful study of the interactions is made as recommended by HRI research (Kim et al., 2011).

The iterative UCD process and UCD phases above were used to define and explore the research questions detailed below. The research questions can be broken down as follows:

RQ1: Can a robotic embodiment impact the perception of an OLM and encourage a learner to reflect on their skills?

- How can a social robot support teachers and learners and fit into the complex classroom environment?
- How do teachers scaffold SRL skills in a paper based prototype?
- Is the prototype geography activity a suitable activity?
- How could a robotic embodiment support delivery of feedback to prompt reflection with the support of an OLM?
- How are the robot, OLM, and learning task perceived by the users?
- How to design the learner model, OLM and learning task to provide an environment to best support the development of SRL skills?

RQ2: Can a robot computationally detect and model reflection and SRL skills of a learner in real time? Can this computational model be used to improve the personalisation and adaptability of a robotic tutor?

- How would experienced teachers use the OLM and learning task to support SRL skills?
- How to detect and model reflection and SRL skills of a learner in real time?
- How can a robotic tutor adapt to individual differences?

- How teachers engage and motivate students to engage in SRL learning skills?
- What do good and poor SRL behaviours look like in this domain?

RQ3: Does the personalised SRL scaffolding delivered by a robotic tutor impact learners' perception of the robot, activity, motivation, SRL skills and learning gain in both short-term and longer-term interactions?

- Do different levels of personalisation of SRL scaffolding impact learners' perception of the robot, activity, motivation, SRL skills and learning gain?
- How does adaptive SRL scaffolding compare to adaptive domain support?
- Does longer-term adaptive SRL scaffolding make a lasting improvement on learners' SRL skills and learning gain?

The main goal of the iterations in the UCD process was to answer the research questions detailed above. The structure of the iterations are similar to the iterations in informant design (Scaife et al., 1997): moving from the 'definition of the domain and problems', through 'translation of a specification', to 'design and test low-tech materials', and finally to 'designing and testing hi-tech prototypes'. This progression is also recommended by the TORMES methodology (Santos and Boticario, 2015): moving from 'Proof of Concept', to 'Elicitation of educational recommendations', and to 'Delivery of recommendations'. These research questions and iterations also look to have user input to ensure the correct robot adaptation to the learners. Guidelines from the 'layered' methodology (Paramythis et al., 2010) suggest that there should be evaluation at several different 'layers' of the system as well as an evaluation of the whole system being evaluated together.

The iterations are as follows:

Iteration 1: Context of use

Goal: The goal of this initial iteration was to identify the context of use and understand how a social robot supports teachers and learners and how it might fit into the complex classroom environment. As such the initial iteration seeks to partially answer RQ1 and further define it. It was essential to engage the end users and to understand the needs of teachers and learners in the learning scenario. It was also used to identify personalised pedagogical strategies from human interactions.

Planning: The main UCD activity in the planning phase was to conduct initial teacher interviews (section 3.4). This was used to create a specification for the learning scenario and the role of the robotic tutor. The teachers specified that the robotic tutor should support SRL skills in an open-ended learning activity using competency based feedback.

Development and Implementation: Based on the specifications from the teachers and a review of literature and existing activities a pilot study was developed to better understand how teachers could support a learner to develop SRL skills. A paper based prototype of a learning activity was developed. The study was developed to investigate how teachers would use the prototype and interaction to scaffold SRL skills (section 3.5).

Evaluation: The study was carried out at the users' school. The evaluation was concerned with the interaction between the learner and the teacher. It was used to identify a number of pedagogical strategies that the teacher used to adapt SRL support to learners of different abilities. Additionally it was used to check that the prototype geography activity was a suitable activity.

This iteration was similar to the 'proof of concept' iteration in the TORMES (Santos and Boticario, 2015) methodology. This also meets the DG1 to involve users (teachers and learners) in the design of the robot and the learning scenario. In particular the teachers were instrumental in setting the context and role of the robot.

Iteration 2: Robotic embodiment

Goal: The goal of this iteration was to investigate how the capabilities of the robotic embodiment are perceived by the learner. It seeks to further answer RQ1 and understand how a robotic embodiment could support delivery of feedback to prompt reflection. In addition, the needs of the learners are also considered in relation to the learning activity.

Planning: The planning of this iteration was based on analysis of the studies undertaken in the previous iteration and a review of the literature. The previous studies highlighted that teachers prompted learners to reflect on their skills and that an OLM could be used to prompt reflection. This provided the research question of how could a robotic embodiment support delivery of feedback to prompt reflection with the support of an OLM?

Development and Implementation: A study was designed to investigate the effect of different levels of robot embodiment on the perception of OLM and skill based feedback in study 3: embodied OLM study (section 3.6). To support this study, initial versions of the learning task, learner model, OLM, and robotic behaviours were developed. The learning task was built upon the paper prototype developed in the previous iteration.

Evaluation: The evaluation of the study focused on how the robot, OLM, and the learning task were perceived by the users. However as recommended in the 'layered' methodology (Paramythis et al., 2010), this was also an opportunity to test the validity of the system's monitoring and evaluation of the learner. The evaluation investigated how well the learner could comprehend the information in the OLM. It found that engagement and trust were greater when some items were displayed onscreen with some feedback given verbally by the robot. This is an important aspect of the interaction between the robot and the learner and the findings were used to further refine the development of the system.

In summary, this was an important iteration for better understanding the needs of the learner rather than the teacher, who was the focus of the previous iteration.

Iteration 3: Identify personalised pedagogical strategies from human interactions

Goal: The goal of this iteration was to identify personalised pedagogical strategies from human interactions to fulfil DG3. It seeks to start to answer RQ2: How would experienced teachers use the OLM and learning task to support SRL skills? The results will be used to create models for the adaptation of the robot to the learner (Paramythis et al., 2010).

Planning: The planning of this iteration was based on an attempt to better understand how teachers could use the system developed in the previous iteration to meet their own and the learners' needs. It seeks to start to answer RQ2: How teachers engage and motivate students to engage in SRL learning skills? What do good and poor SRL behaviours look like in this domain? Requirements were also available from the previous iterations concerning the contents that should be visible in the OLM.

Development and Implementation: A HHI study was designed to investigate how teachers use the OLM and activity to scaffold SRL in study 4: UCD teacher study (section 3.7). This required a more open-ended learning activity and a more inspectable OLM than the previous iteration to be developed. The findings from previous iterations and a review of literature and other activities led to the development of a learning task where learners can demonstrate SRL skills essential for real time modelling. The specification, design, and implementation details of the learner model, OLM and learning task are described in chapter 4.

Evaluation: The evaluation of the study focused on interaction between the teacher and the learner. Analysis of video recordings and logs from the learning activity were used in the analysis. Observation of an experienced human teacher using the OLM to provide SRL support to learners showed that this would be a valid approach for the robotic tutor to follow, and also provided the basis of how the robot uses OLM to motivate and personalise SRL support. It was also possible to evaluate if the implementation of a learning scenario could support the cognitive development of SRL skills in learners of the target age group. It was also another opportunity to check the collection of data, the validity of the systems monitoring, interpretation, and modelling of the learner (Paramythis et al., 2010).

This iteration is similar to the 'Elicitation of educational recommendations' phase from the TORMES (Santos and Boticario, 2015) methodology, it was used to produce diverse pedagogical strategy recommendations for the robotic tutor. The recommendations were then used to develop the pedagogical model in the next iteration. This phase was able to assist in understanding the needs of both teachers and learners.

Iteration 4: Personalised SRL scaffolding

Goal: The goal of this iteration is to answer both RQ2 and RQ3: Can a robot computationally detect and model reflection and SRL skills of a learner in real time? Can this computational model be used to improve the personalisation and adaptability of a robotic tutor? Does the personalised SRL scaffolding delivered by a robotic tutor impact learners' perception of the robot, activity, motivation, SRL skills and learning gain in short-term interactions? It also aims to meet DG4 to effectively tie the robot capabilities to well supported pedagogical theories.

Planning: The planning focuses on creating a specification from the requirements in the previous iteration. This involved reviewing theories for scaffolding SRL and linking them with the observations of the teacher and learner from the previous UCD studies, primarily the observations from HHI studies described in study 2 (section 3.5) and study 4 (section 3.7) with the SRL scaffolding theory. This created an observational and theoretical basis for the development and implementation of the computational model of SRL. This process is described in detail in section 5.1.

The planning was also concerned with ensuring that the adaptation to the learner was correct.

Development and Implementation: A HRI study was designed to evaluate different levels of adaptive support described in study 5: adaptive SRL study (section 6.2). This required the design and implementation of the pedagogical model and autonomous robot behaviours described in section 5.2.

Evaluation: The evaluation focused on the user's experience with the robotic tutor with different levels of adaptive SRL support. The measures for the evaluation are detailed in section 6.1. The evaluation indicates that it is possible to detect and model reflection and SRL skills of a learner in real time. It was observed that adaptive SRL support provided by the robotic tutor and OLM prompts the learner to reflect and motivates the learner to choose appropriate task strategies. Conversely, highlighting issues but not providing a sufficient level of support makes the learners feel higher levels of stress and pressure and may cause them to become disengaged. This level of adaptation was then taken forward into the next iteration.

This iteration is similar to the 'Delivery of recommendations' phase from the TORMES (Santos and Boticario, 2015) methodology, it was used to evaluate personalised support from a robotic tutor. This iteration helped understand the needs of the learners. As recommended in the 'layered' methodology (Paramythis et al., 2010), this iteration was used to evaluate the high-level adaptation decisions as well as how those adaptation decisions were made.

Iteration 5: Longer-term personalised SRL scaffolding

Goal: The goal of this iteration is to answer RQ3: Does the personalised SRL scaffolding delivered by a robotic tutor impact learners' perception of the robot, activity, motivation, SRL skills and learning gain in longer-term interactions? How does adaptive SRL scaffolding compare to adaptive domain support? Does longer-term adaptive SRL scaffolding make a lasting improvement on learners' SRL skills and learning gain?

Planning: The planning focused on extending the SRL scaffolding and making it suitable for longer-term interactions. Longer-term behaviours were based on observations made on the teachers in previous UCD studies. A key requirement identified from the literature was to not only support SRL in the interaction but to also investigate if the SRL could transfer to different types of activities and most importantly into the SRL attitudes of the learner.

Development and Implementation: The literature on longer-term interaction was reviewed. A longer-term HRI study was designed to compare adaptive SRL scaffolding to adaptive domain support (section 6.3). The development contained the addition of wrap-up and summaries to support longer-term interactions. The learning task was also extended to include more activities. This enabled the evaluation of transfer learning within the learning task.

Evaluation: The evaluation focused on the user's experience with the robotic tutor between adaptive SRL scaffolding with domain support and a robot with adaptive domain support alone. The measures for the evaluation are detailed in section 6.1. In addition, the learners were asked questions regarding their SRL attitudes. It was observed that adaptive SRL scaffolding is more effective than adaptive domain scaffolding in increasing learning gain and SRL learning attitudes.

Again this iteration is similar to the 'Delivery of recommendations' phase from the TORMES (Santos and Boticario, 2015) methodology. This iteration is the final summative evaluation of the research presented in this thesis. As recommended in the 'layered' methodology (Paramythis et al., 2010), this iteration was used to evaluate the high-level adaptation decisions as well as how those adaptation decisions were made.

The links between the iterations of the UCD process, research questions, design activities, studies, and contributions are presented in Table 3.1, Table 3.2, and Table 3.3 which explain the iterative flow of the research process. The tables also highlight how the design of the system and the evaluation studies are informed by the design activities.

Table 3.1: Iterative flow of research process (a) is explained by the links between the iterations of the UCD process, research questions, design activities, studies, and contributions

Iteration	Research questions	Design activity/study	Results
1	• How can a social robot support teachers and learners and fit into the complex classroom environment?	Teachers were asked about the role of a *social robotic tutor* and how teachers provided personalised support to learners in study 1: teacher interviews (section 3.4)	• Teachers would like learners to develop SRL skills. • Robotic tutor could support SRL skills. • Open-ended activity best for SRL skills. • Competency based feedback good for SRL skills.
1	• How do teachers scaffold SRL skills in a paper based prototype? • Is the prototype geography activity a suitable activity?	An expert teacher was asked to support learners of different abilities through a paper based prototype activity while focusing on supporting SRL skills in study 2: mock-up study (section 3.5)	• Identified a number of pedagogical strategies that the teacher used to adapt SRL support to learners of different abilities. • A key strategy was for teachers to prompt the learner to reflect on their map reading competencies. • Learning activity was appropriate for learners to demonstrate SRL skills. • Formative feedback for further development of the activity.
2	• How could a robotic embodiment support delivery of feedback to prompt reflection with the support of an OLM? • How are the robot, OLM, and the activity perceived by the users?	The previous studies highlighted that teachers prompted the learners to reflect on their skills. The effect of different level of robot embodiment on perception of OLM and skill based feedback is explored in study 3: embodied OLM study (section 3.6)	• There was a preference for mixed feedback. • Some information should be presented in the on-screen OLM. • The robotic tutor should explain and elaborate on the information in the OLM when needed.

Table 3.2: Iterative flow of research process (b) is explained by the links between the iterations of the UCD process, research questions, design activities, studies, and contributions

Iter-ation	Research questions	Design activity/study	Results
3	• How to design the learner model, OLM and learning task to provide an environment to best support the development of SRL skills?	The design process and implementation details of the learner model, OLM and learning task are detailed in chapter 4. Literature is reviewed regarding implementation of learner model, OLM and learning task to allow SRL development for this age of children	• Implementation of a learning scenario that can support the cognitive development of SRL skills in learners of the target age group.
3	• How would experienced teachers use the OLM and learning task to support SRL skills? • How teachers engage and motivate students to engage in SRL learning skills? • What do good and poor SRL behaviours look like in the domain?	A HHI study where teachers use the OLM and activity to scaffold SRL is conducted in study 4: UCD teacher study (section 3.7). Video and activity logs are recorded in the interactions.	• Examples from teachers of behaviours for social co-regulation of SRL skills. • Examples where the teachers balanced personalised domain, motivational and SRL support.
4	• How to detect and model reflection and SRL skills of a learner in real time? • How can a robotic tutor adapt to individual differences?	The development of an ideal SRL model is described in section 5.2 and section 5.1. Observations from HHI studies in study 2 (section 3.5) and study 4 (section 3.7) are merged with the SRL scaffolding theory	• An observational and theoretical basis for the development and implementation of the computational model of SRL.

Table 3.3: Iterative flow of research process (c) is explained by the links between the iterations of the UCD process, research questions, design activities, studies, and contributions

Iteration	Research questions	Design activity/study	Results
4	• Do different levels of personalisation of SRL scaffolding impact learners' perception of the robot, activity, motivation, SRL skills and learning gain?	A short-term evaluation with different levels of adaptive support is described in study 5: adaptive SRL study (section 6.2).	• Significant improvement in learning gain in the adaptive SRL scaffolding condition over the OLM only and the control conditions. • Adaptive SRL support provided by the robotic tutor and OLM prompts the learner to reflect and motivates the learner to choose appropriate task strategies. • High level indicators of high level SRL skills in this learning context.
5	• How does adaptive SRL scaffolding compare to adaptive domain support? • Does longer-term adaptive SRL scaffolding make a lasting improvement on learners' SRL skills and learning gain?	A longer-term evaluation is described in Study 6: longer-term SRL study (section 6.3) where adaptive SRL scaffolding is compared to adaptive domain support.	• Adaptive SRL scaffolding is more effective than adaptive domain scaffolding in increasing SRL behaviours.

3.3 Methodological considerations

This section describes some of the methodological considerations that arise from the UCD approach. This chapter has argued for the importance of including users in the design and evaluation of HRI. If possible the research should take place in a school setting in the context of a real course to be more ecologically valid (Koedinger et al., 2009). This section aims to provide some practical advice for undertaking such studies within the school environment.

3.3.1 Recruitment of schools, teachers, and students

This section presents recruitment details and strategy. The recruitment strategy was to establish relationships with local schools, initially for feedback on the design of the learning scenario and robotic tutor, moving on to performing more in-depth studies as the system was developed.

Local schools were contacted through emails and follow up phone calls, an example recruitment email is presented in section 8.1.4. The West Midlands STEM Ambassador Hub[1] offers support to develop links between schools and individuals working to enhance young people's science, technology, engineering and mathematics (STEM) education. By contacting the STEM ambassador hub it was possible to attend events and contact schools that were already keen to work with researchers and expose their students to science and higher education.

Additionally a Post Graduate Researcher presentation was developed with support from the University of Birmingham's Outreach office. The presentation contained videos of state of the art robots, a live demonstration of the NAO robotic tutor, and an interactive robot design activity. This presentation was delivered to schools visiting the University of Birmingham. The presentation was also offered and delivered at the schools contacted directly and through the STEM Ambassador

[1]https://www.stem.org.uk/

Hub.

Recruitment of teachers and students was more likely to succeed outside of exam season. The key exams in the UK are; Key Stage 1 SATs in Year 2 at age 7; Key Stage 2 SATs in Year 6 at age 11; and GCSEs in Key Stage 4 in Year 11 at age 16. Students take fewer exams between ages 7 and 14 (Year 3 to 9) after they have taken the KS1 SATs but before preparation for GCSEs at age 14. Children in Year 6 start preparing for KS2 SATs in November and take the test in May, but it was possible to recruit teachers and students in this year group if studies occur before October and after May.

3.3.2 Procedural design

All of the studies presented in this thesis took place in the users' school around the teachers' and learners' normal working day. Communication with the schools was essential to ensure that the studies would fit around the teachers and learners causing as little disruption as possible. This meant being aware of the school's timetable to schedule sessions that did not clash with lesson change over times.

The design of the learning activity was also created to be relevant to the England and Wales national curriculum for geography (DfE, 2014) to ensure it was a relevant exercise for the students to take part in.

Experimental setup

As the availability of space in schools can be an issue, often involving changing meeting or class rooms, the experimental setup must be flexible and portable.

The set up of electrical equipment also needs to be carefully considered as there are not always power outlets in easy to access positions. Extension cables and tape to secure the cabling should make up part of the experimental setup to ensure that the setup is as straight forward and safe as possible.

Data collection and questionnaires

The types of skills and the questionnaires that students are required to answer must also be considered. For this thesis students between the ages 10 and 12 were recruited as they were able to understand and answer the questions required. This age range is also noted as a key age for when students are developing SRL skills (Ferreira and Simão, 2012).

Time constraints must also be considered. It can take up a large part of an individual session for a learner to answer self-assessment tests. One solution is to request that teachers administer tests to all students prior to the study at the same in class, which leaves more time in the session for interaction with the robotic tutor. If this is not possible and if there are multiple rooms available for the study, one student can be carrying out a test or questionnaire when another is interacting with the robotic tutor.

It is also important to consider the most important questions to ask in the questionnaire. There is simply not enough time, it may be too taxing, or might be too stressful to give students a complete battery of tests (domain test, personality test, SRL test, perform the study, and then further user experience questions) so the test and questionnaires need to be very carefully thought out and limited to best answer research questions. Stealth assessment (Sabourin and Lynne, 2013) can also be used as a alternative or in conjunction with questionnaires to measure important characteristics from interactions with the learning task without interrupting the learners engagement and flow.

Technical considerations

There are technical challenges to be aware of when working in a school environment. As mentioned previously it can be hard to find suitable locations in a school to run experiments, so technical solutions should be as flexible and reliable as possible. The use of sensors is not encouraged due to the many sources of interference that can happen at a school. Schools can be loud and noisy and this will effect the reliability of sound based sensors that might be used for voice recognition. Infrared depth sensors and camera reliability can be effected by poor lighting conditions or windows that can't be covered. The ability to access the Internet or computer network should not be assumed either. Where possible, liaising with a schools IT technician may be a helpful exercise.

3.3.3 Ethical considerations

The details of the ethical approval are presented in section 1.3, with further details including recruitment, participant information, and consent materials presented in section 8.1.

The studies were planned to cause as little disruption as possible to the students by fitting around the school timetable and not causing the children to take too much time out of class. The studies were also designed to be as stress free as possible. If a child did not want to take part in the study they could cease the session at any point. The children were not deceived in any way about the capabilities of the robot tutor.

Where possible no child was excluded from the studies, the teachers were requested to allow all children in a class to participate in the studies. After all of the participants had taken part in the studies the students were given the opportunity to interact with the robot.

In many cases the teachers were very keen to have the robotic tutor and the study in their classroom with the added benefit of sparking the children's interest in science and higher education. The subject matter of the study was also linked to the student's curriculum so it was a useful exercise for the learner.

The remainder of this chapter describes each of the studies in detail.

3.4 Study 1: teacher interviews

3.4.1 Introduction

This UCD study aims to elicit requirements, and create a specification to inform the design of the learning task, OLM, and robotic tutor. Teacher interviews were undertaken to investigate teachers' perspectives for scaffolding SRL in open-ended tasks using an OLM together with a robot (Jones et al., 2013). The potential for scaffolding SRL in open-ended learning scenarios using a robotic tutor and an OLM is considered.

Motivation

The motivation for this study is to better understand teachers' perspectives on how to develop a socially acceptable robotic tutor for use in the classroom. The questions are based on the open questions raised in a review of robots in education (Mubin et al., 2013), such as the role of the robotic tutor and how to adapt behaviour and curriculum to the learner. Teachers were interviewed with the aim of understanding their perspectives on the potential for scaffolding SRL with an OLM and a robotic tutor, and to derive suggestions the for design of the learning scenario and robotic tutor. This is a similar approach to the EMOTE project which explored both teachers' (Serholt et al., 2014a) and learners' (Serholt and Barendregt, 2014) needs.

Research questions

The aims of this study are to understand how a social robot can support teachers and learners and fit into the complex classroom environment. The questions focused on the plausibility of having a robotic tutor in a classroom and how it could support child learning.

3.4.2 Method

Schools and teachers were approached and recruited as described in subsection 3.3.1, where the aims of the research project were described to the schools and teachers. Following recruitment a meeting was arranged with the teachers to take place at the teacher's school. This is a qualitative study with a thematic analysis.

Participants

Seven participants took part in open interviews (4 teachers, 2 teaching assistants, 1 trainee teacher), in 6 separate interviews. The details of the demographic information and interviews is shown in Table 3.4. In accordance with the ethics procedure, informed consent was obtained in writing from the teachers participating in the study as outlined in subsection 8.1.2. [redacted]

Table 3.4: Participant details for study 1: teacher interviews. Gender, age, teaching experience, and current position

Gender	Age	Years Teaching Experience	Position	Interview
F	58	36	Deputy head teacher	1
F	57	25	Teaching assistant and special education needs coordinator	2
F	55	21	Head teaching assistant	3
M	54	32	Head of Geography	4
M	33	10	Teacher	5
M	22	1	Trainee Teacher	5
M	39	15	Teacher	6

Procedure

The interviews were held in meeting rooms at the teachers' schools. In each interview the aims of the interview were described, highlighting the objectives to explore how to personalise robotic tutoring to the learner's needs, and understanding the curriculum that the robot could help deliver. The teachers were also made aware of the possibility of using a touchscreen table to display a geography activity and skill meters to aid interaction with a robot. In a semi-formal interview, specific questions relevant to scaffolding and OLMs included:

- What role would a system like this play? (To ascertain teachers' views on how the robot could effectively 'fit' into the classroom and classroom practice). This question was also designed to prompt the teachers to talk about the learning activity and curriculum that the robotic tutor could help support.
- If you had a robot that could monitor how a child is progressing, how would you like that robot to interact with the child? (To provide information for the design of the learning scenarios and robot interactions).
- Would it be beneficial to set the level of difficulty of the task? How do you do this at the moment? (To gauge the extent of teachers' likely acceptance of a coarse grained personalisation approach with a robotic tutor).
- How do you detect when a student is having difficulties and how do you help the learner overcome the difficulties? (To ascertain how teachers detect when a learner is facing difficulties in this kind of open-ended activity, and whether they may be receptive to more fine grained adaptation with the robotic tutor).

The interviews lasted between 10 and 30 minutes. The full list of questions is in section 8.2. All participants were asked all of the questions to ensure that they were able to provide an input.

Data collection

Audio recordings were made by the author. Written notes were made by the researcher in addition to the audio recordings.

3.4.3 Results

Data Analysis

The audio recordings were transcribed and the written notes reviewed by the author. The teachers comments were then categorised in relation to the questions asked. A thematic analysis was performed where patterns in the comments were found. Similar comments were grouped together and used to identify common categories. A spreadsheet was used to support this process.

Teacher comments

Table 3.5 summarises the number of teachers expressing each of the points addressed below, following the comment categorisations, with representative viewpoints then discussed further.

Table 3.5: Teacher comments categorised for study 1: teacher interviews

Comment	No. teachers
Personalisation	7
Formative feedback	2
More open-ended activities	7
Prompting meta-cognitive behaviours	7
Encourage self-regulated learning	3
Incorporation of robot into classroom	7

Personalised tutoring. Teachers try to personalise or adapt the material to address the varied needs of students. Typically the teachers change the difficulty of an activity by changing the language style, the number of prompts, breaking down the activity into smaller steps, and the amount of scaffolding provided. The most difficult questions or problems may be very open-ended, and require the learner to argue a point in their own words, or the teacher may apply extra constraints such as working within a budget. Teachers might also give out different question sheets to different students. All teachers were emphatic that the system to be trialled should be able to respond to the individual, stretching the most able while also ensuring suitable personalisation for the less advanced students.

Formative feedback. Two teachers suggested that progress bars may be beneficial. They stressed that real time assessment would be desirable, and if a learner faced difficulties, these need to be caught promptly and acted upon as appropriate by the system or the teacher. This could be argued as support for an on-screen OLM.

More open-ended activities. In addition, all teachers stated that they would like the learning activities to move easily beyond basic map reading skills to activities where the learner needs to make comparisons, decisions and arguments. Decisions and arguments could be made on tasks which involve e.g. deciding on the most appropriate location for a visitor centre or flood defence: the learner must make an argument in favour or against an action. Thus, the teachers are looking for ways to incorporate more open-ended activities into the classroom interaction.

Prompting meta-cognitive behaviours. All teachers wanted to encourage reflection and meta-cognitive behaviours e.g. by prompting with phrases such as "Have a think", "Did you consider…?". They also stressed that the robot should make it clear in the relevant activities when there is no right or wrong answer.

Self-regulated learning. Several teachers were very interested in using the system to encourage independent learning, as this is becoming a key objective for teachers.

Incorporation of robot into classroom. There were no concerns from any of the teachers about fitting the robot into the classroom activities, particularly if the lesson plan actively included the robot (e.g. in a station rotation lesson where a number of learners in a class would have a turn with the robot). The teachers were interested in monitoring the learner's progress from a console, enabling the teacher to intervene if the learner stopped making progress. This would be particularly useful if there were multiple learners interacting with multiple artificial tutors. They also thought that the simple fact that there was a robot would make any task seem novel and more engaging.

3.4.4 Discussion

Because the interviews were open, not all points were discussed in each interview. The lower level of comments in some areas therefore may not indicate disagreement, but rather that these issues were not raised during the interview.

The possibility for the robot to adapt to individuals, as requested by all participants, is exactly the kind of approach enabled by a learner model. For this reason the learner model is anticipated to be acceptable to teachers in this robot and table top context. All teachers also wished to use open-ended tasks such as described above, to match the requirements of the England and Wales national curriculum for geography (DfE, 2014). This is, therefore, another indication of likely acceptance.

The fact that two teachers suggested progress bars indicates that these participants wish to have a view of learning visible on the table top, in line with OLM. In addition, the OLM should facilitate the kind of meta-cognitive behaviours considered important by all teachers. The request for being able to monitor learners is in line with OLM also being a tool to support teachers (Reimann et al., 2012). This goes beyond many learning analytics visualisations (e.g. dashboards (Verbert et al., 2013)) to focus on supporting an understanding of competencies.

An important immediate concern is practical deployment in the existing learning context and curriculum. All teachers could see how the robot and touchscreen table could be integrated into the classroom and could identify benefits for doing so. Thus, there is a role for robots and OLMs in scaffolding open-ended learning.

The teachers also provided examples of social interactions and scaffolding between the learner and the robot. These included:

- In addition to the learner model visualisations on the table top, the robot can itself express the model content by giving a summary of relevant knowledge or competencies;

- Offering assistance by guiding the learner through instructions;
- Asking questions (to prompt reflection);
- Gestures (to illustrate or focus attention, or indicate shared focus);
- Offering affective support if learners' actions are not optimal (telling them not to worry and try again); and
- Drawing attention back to the task if a learner becomes distracted.

3.4.5 Summary and conclusions

This study has captured teachers' perspectives on how to develop a socially acceptable robotic tutor for use in the classroom. The teachers were particularly interested in how the robotic tutor could support or motivate the learners to become better independent learners in more open-ended learning scenarios. An argument has been presented for the benefits of using an OLM as a means to scaffold learners' development of self-regulation skills and meta-cognitive behaviours in open-ended learning contexts, considered important by the teachers. This type of scaffolding is becoming increasingly central to supporting the competency focus adopted in many subjects. Because of the advantages of *social robotic tutors*, a SAR approach is proposed. The teacher interviews confirmed the feasibility of introducing this solution to real classrooms that have the appropriate technologies.

The findings regarding the learning scenario and learner model visualisations are incorporated in the design of the activity in the mock-up study (section 3.5), the embodiment study (section 3.6), and the design of the learning scenario in (chapter 4). The teachers gave examples of social interactions and scaffolding that informed the development of the pedagogical strategies and tactics described in subsection 5.2.2.

3.5 Study 2: mock-up study

3.5.1 Introduction

This mock-up study involves a teacher helping individual learners with varying abilities through a paper based version of the learning task. This UCD study aids the development of the learning scenario and also offers an initial understanding of how and when teachers provide personalised feedback to the learners in this type of activity.

Motivation

A mock-up is a prototype that enables testing and design of some functionality of a system (Bartneck and Hu, 2004). A mock-up allows the evaluation and elicitation of feedback on the learning task and capture a corpus of data that will aid in the design of the learning task to be implemented on the touchscreen table and suitable actions for the robotic tutor. It was observed in the initial teacher interviews that it can be difficult for teachers to explain in detail how they would adjust to different students' needs on the basis of an abstract description of the task. A mock-up allows the study of how teachers adapt their pedagogical strategies to respond to individual students' needs in this particular learning scenario. Additionally, this type of UCD study is needed, as while there is a lot of theoretical literature regarding the support of SRL skills, it is not always clear how to practically apply it to a specific domain or learning scenario.

Research questions

The first research question is to understand if the learning scenario could support the development of SRL skills. Additionally, is the content, design and difficulty level appropriate for the learners. The second research question focuses on how teachers support domain learning and SRL skills in practice in this domain. The aim is to gather utterances and behavioural data from the teachers and students in order to inform the robotic tutor's perceptive capabilities as well as pedagogical approach.

3.5.2 Method

An experienced teacher was asked to work with three 12 year old students individually on a paper based educational activity. Schools and teachers were approached and recruited as described in subsection 3.3.1. This is a qualitative study with a thematic analysis.

Participants

The participants of this study were three students of varying ability aged 12 years old and one experienced teacher. The teacher was the head of the geography department. The teacher was male, 54 years old, with 32 years of teaching experience. The teacher was asked to select three students of different ability to increase the chance of observing different teaching styles. There were two female students and one male student selected. In accordance with the ethics procedure, informed consent was obtained in writing from the teachers, parents, and the children participating in the study as outlined in subsection 8.1.2. The ethics protocol number for this study is ERN_13–0489, the relevant documentation can be seen in Figure 8.2.

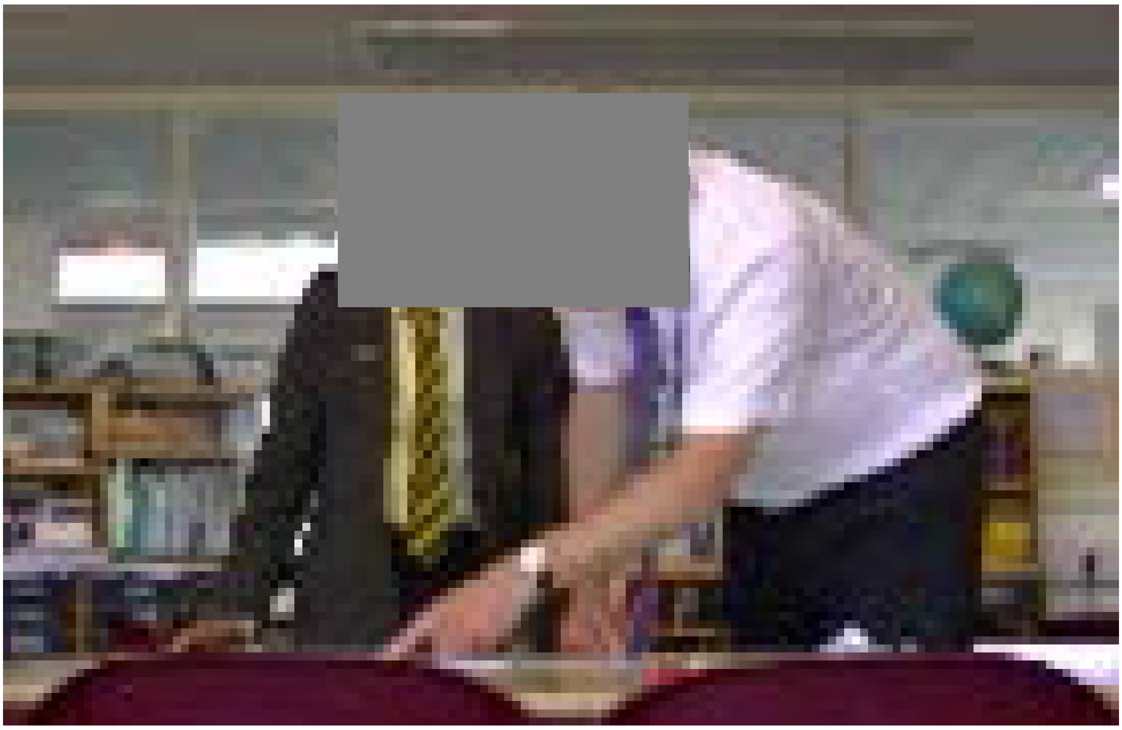

Figure 3.2: Teacher and student taking part in study 2: mock-up study

Procedure

The teacher was emailed the learning activity in advance. Prior to the session, the teacher was given some time to familiarise themselves with the learning activity. Each session with a learner was 30 minutes in duration. The teacher began by introducing the activity to the learner. The teacher then supported the learner as they completed the trail in the activity. Finally, an open-ended interview was held with the teacher and learner to elicit their input on the activity. This procedure is shown in Table 3.6

Experimental setup

The study took place in a classroom in the teacher and learners' school. The following material was used: instructions for the teacher; a local map; a topographical map (Figure 3.4); a compass; a scale for measuring straight distances; colouring pencils; 2 cameras (one capturing the overall situation and one focusing on the participants'

Table 3.6: Procedure for Study 2

Activity	Notes
Teacher briefing	Teacher given time to review the learning activity
Learner briefing	Teacher selected participants, consent forms and information sent to learners parents for approval
Teacher introduces activity to learner	Teacher introduces activity to learner and shows the learner the activity and the tools
Learning session	Teacher supports the learner as they complete the trail in the activity
Interview	The learner and teacher are asked for feedback on the activity

faces); and an external table microphone. The arrangement of materials is shown in Figure 3.3.

The activity was based on requirements gathered in section 3.4. The activity was adapted to the local area of the school in which the mock-up sessions were held. The instructions and full activity trail is given in the Appendix (section 8.3). An image of the activity is shown in Figure 3.4.

Data collection

Audio and video recordings were made by the researcher. Two cameras were used, one capturing the overall situation and one focusing on the participants' faces.

3.5.3 Results

Data Analysis

The video and audio recordings were transcribed and reviewed by the author. The transcription of the video was supported with the ELAN software (Wittenburg et al., 2006). A thematic analysis was performed where patterns in the teacher's and learners' actions were found. Similar comments were grouped together and used to identify common categories. A spreadsheet was used to support this process.

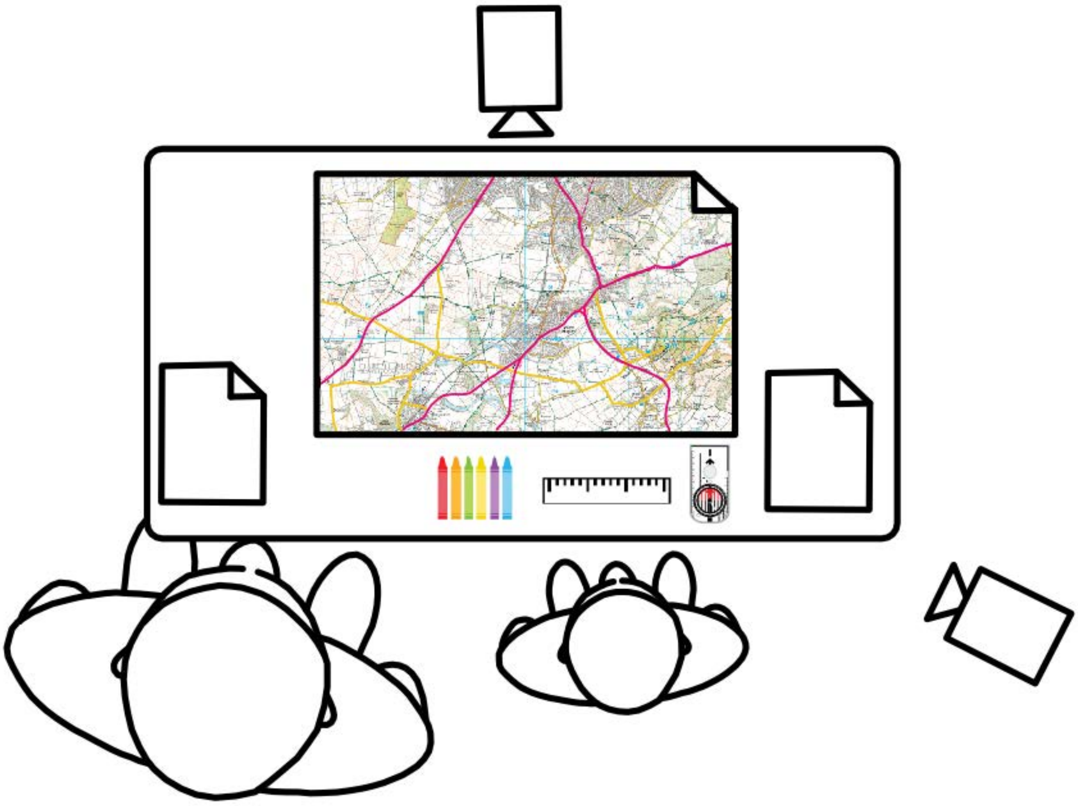

Figure 3.3: Setup study 2: mock-up study

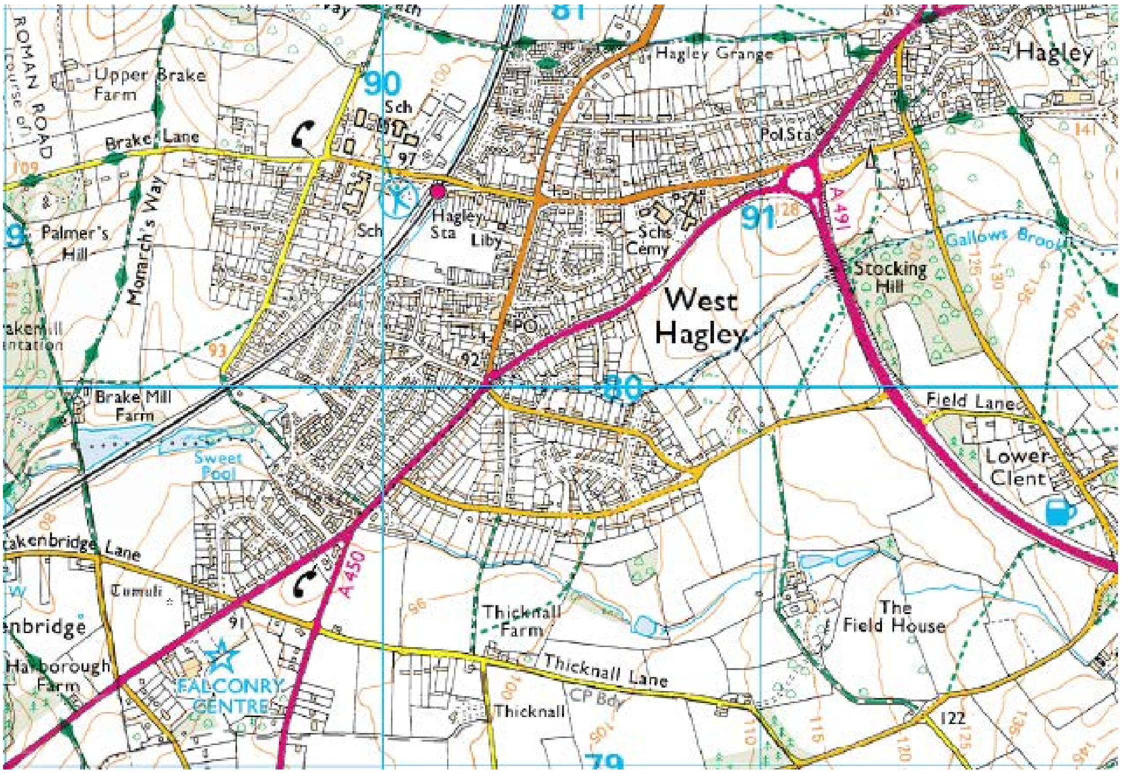

Figure 3.4: Paper activity for study 2: mock-up study

Observations

The following observations were made regarding how the teacher supported the students during the activity.

Support for SRL. The teacher would try to allow the student to take the lead and be as independent as possible. The teacher tried not to give the answer, but would keep probing and asking questions to prompt reflection until the student understood the question and would guide the student towards the answer. The teacher would move from discovery to guided learning, so the student would be allowed space to solve the problem themselves, but if they started to make mistakes or it was clear that they were getting stuck the teacher would support the student. The teacher asks questions to encourage reflection rather than providing correct answers. The teachers would offer support in a subtle way by handing over or sliding important tools in front of the students if they neglect to use them.

Support for motivation. The teacher wanted the student to be engaged and motivated to complete the task. If the student became stuck or disengaged they would offer support. The teacher would try to make the task more engaging by adding context and bringing the map to life. An example of this is by relating the map to objects in the world, such as features that the student could see from the window, or was familiar with. The teacher also showed that they were interested in the student by leaning forward and looking at the map when the student was using the tools. Additionally, after each correct move, the teacher made supportive comments such as, “Good”, “Exactly”, “Very good”. This provides the student with positive feedback and an awareness that their skills are increasing.

General tutoring. The teacher also provided domain help and general tutoring support. The first thing the teacher wanted to establish was that the student understood the question. The teacher would often prompt students to read the question in more detail if they were making a mistake or taking time. Sometimes, the teacher would ask the student to explain the question back. The teacher would also repeat keywords from the question. If the student started to struggle then the teacher would break the task down into smaller components. Finally, if the student did not have experience with a tool, or if the difficulty of the task increased beyond that which the student was familiar, then the teacher would give tutorials e.g. how to use the compass.

Non-verbal behaviours. The teacher also appeared to offer a lot of non-verbal feedback. The teacher was clearly interested and attentive to what the student was doing. There was also a lot of gesturing involved with explaining concepts and giving domain help on the map activity.

3.5.4 Summary and conclusions

The observations derived from this study certainly show that this type of activity allows the learner to demonstrate SRL skills and it also allows the teacher to support the learner in deploying the SRL skills. The activity seems to be set at approximately the right level of difficulty as the students were able to complete the activity even though they may have required a little support. The findings are used to continue the development of the activity in subsection 4.2.1.

The findings enabled a better understanding of the dynamics between the teacher, task, and learner. There are examples of more detailed pedagogical tactics and strategies employed by the teacher. The teacher's contributions included ideas for pedagogical strategies and tactics described in subsection 5.2.2, e.g. the teacher would try to allow the student to take the lead and be as independent as possible, preferring for the students to reflect and direct their own learning. However at the same time the teacher was clearly concerned with the development of the learner's skills, the teacher wanted the learner to practice using the tools and would try to support the learner in selecting and practising with the appropriate tools. This finding contributes to the inclusion of a competency based feedback. This study supported the understanding of the teachers' ways of approaching the learning task, including their assessment of the difficulty levels of different sub tasks, and how they would personalise their teaching strategy to students of differing ability. The less capable students are provided with simple and clearly formulated pieces of information, while more capable students are provided with one or several complex pieces of information at a time. The teacher was also keen to motivate the students; as a student became proficient at the domain skills the teacher would give them encouraging comments to acknowledge the student's development.

The next study investigates how a robotic embodiment may support the skill or competency based feedback that the teacher delivers in this study.

3.6 Study 3: embodied OLM study

3.6.1 Introduction

This is a UCD study that focuses on the user experience of the learner. Specifically how robotic embodiment effects the usability of the OLM. The previous study focuses on developing the learning scenario and ideas in respect of the feedback and support a robot could provide to the learner. In the previous studies, study 1 (section 3.4) and study 2 (section 3.5), it was observed that teachers would like learners to be aware of their developing skills. Indeed, in the previous study the teacher prompted the learners to reflect on their skills and competencies. Within an ITS a common way to prompt reflection of skill and competencies is with an OLM in the form of skill meters. In the initial teacher interviews (section 3.4) some of the teachers suggested that skill meters might be useful.

The aim of this study is to understand how a robotic embodiment might best support delivery of skill or competency based feedback with support of an OLM. Specifically to investigate the effect of different embodiments on perception of a skill based feedback (a basic OLM) with a robotic tutor. The study aims to understand how the robot's actions may influence how the robot, OLM, and the activity are perceived by the learners. As the learners will be the ones using the robotic tutor and OLM to learn, it is important to understand how the information can be presented in a way that is most user friendly to them.

Each learner carried out a geography based activity on a touchscreen table. A real time model of the learner's skill levels was built based on the learner's interaction with the activity. Three conditions are explored where the contents of this learner model is fed back to the learner with different levels of embodiment: (1) full embodiment, where skill levels are presented and explained solely by a robot; (2) mixed embodiment, where skill levels are presented on a screen with explanation by a robot; and (3) no embodiment, where skill levels and explanation are presented on a screen with no robot.

This study was also an important test of the learning task and scenario as a whole, as this was the first time that the learners had used an electronic version of the learning task.

Motivation

Experienced teachers and computer based learning systems allow a scenario where a learner carries out an activity and receives feedback on their areas of strengths and weaknesses contemporaneously. This scenario enables the learner to reflect, correct any errors, and build upon their strengths as they progress through the activity. This type of one-on-one tutoring benefits the student (VanLehn, 2011). The aim is to emulate such an approach with an interactive activity that can model the skill levels of a learner in real time and provide feedback via a robotic tutor.

A number of systems have used virtual embodiment to teach or interact with the user as compared to text based feedback (Johnson et al., 2000; Dehn and Van Mulken, 2000), although results are mixed in terms of learning gain there are many positive effects gained, such as enjoyment, motivation (Moundridou and Virvou, 2002), and the learners' perception of the learning experience (Lester et al., 1997). Studies that compared virtual representations of characters with robots showed a preference for robotic embodiment with reference to social presence (Kidd, 2003; Lee et al., 2006), enjoyment (Pereira et al., 2008; Kidd and Breazeal, 2004; Wainer et al., 2007), and performance (Hoffmann and Krämer, 2011). Greater learning gains have also been shown with a robotic tutor when compared to a virtual tutor (Leyzberg et al., 2012). The development of trust can also be increased with the presence of embodiment (Hancock et al., 2011).

To help define the future direction of development of the robotic tutor, it was decided that it would be useful to have a robotic tutor with access to an OLM to better support the reflection of the learner. It may be the case that the OLM on-screen would distract or overwhelm the learner, however, it was hoped that the robotic tutor's presence would lead to the learner paying more attention to the OLM than text based feedback alone, as learners may afford greater respect to the robot and pay more attention to the information that it gives (Bainbridge et al., 2008). However, it is also good practice to investigate if the findings from those studies hold with this type of feedback in this context, as potentially the robot could distract from the task in a way that it was feared that virtual agents might (Dehn and Van Mulken, 2000). Understanding which pieces of information are more successfully delivered by a robot and which by onscreen elements is useful for the design of systems that include a robot. The aim is to investigate and measure how and to what extent the learners accept personal skill based feedback from a physical entity when compared with a touchscreen table. One of the factors that may be increased with a robotic embodiment is trust. However, there has been little work empirically in this area comparing automated aids vs robotic aids (Hancock et al., 2011).

Research questions

This study investigates if a robotic tutor is able to present feedback in a more effective way when compared to on-screen feedback alone, or a combination of both a robot tutor and on-screen feedback. To that end this study investigates the effect of different embodiments on the learner's perception of feedback and overall experience. No previous robot tutor research has investigated embodiment on presentation of an OLM.

3.6.2 Method

An initial version of the learning scenario was developed based on teacher feedback from the initial studies in section 3.4 and section 3.5. The learning scenario consists of a touchscreen table running a learning task positioned in front of the learner. The learning task is a geography exercise targeted at 11–13 year old learners. The details of the development and implementation are described in section 4.2. A basic model of the learner's map reading skills is built; the development of this learner model is described in section 4.3.

This study explores three conditions where the contents of this learner model is fed back to the learner in the form of the OLM. The implementation details of the OLM are described in section 4.4. The three conditions have different levels of embodiment: (1) *full embodiment*, where skill levels are presented and explained solely by a robot; (2) *mixed embodiment*, where skill levels are presented onscreen with explanation by a robot; and (3) *no embodiment*, where skill levels and explanation are presented on a screen with no robot. This study is a between subject design.

A series of Likert style questions were asked to investigate enjoyment, perception, and trust of the presentation of the learner model. The findings suggest that embodiment may increase enjoyment, understanding, and trust in explanations of skill levels.

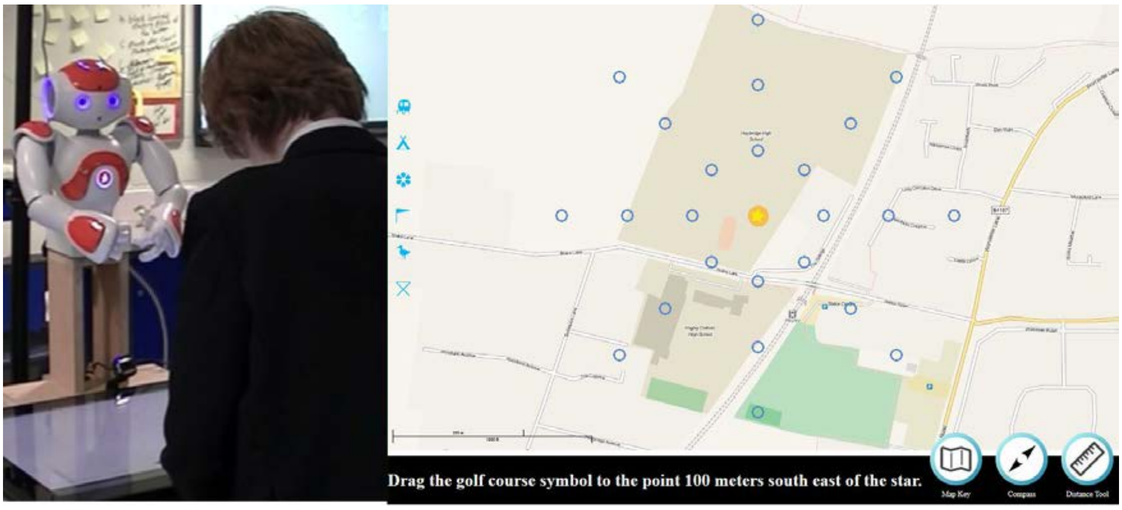

Figure 3.5: NAO robot, learner, and learning task set up for study 3: embodied OLM study

Participants

Schools and teachers were approached and recruited as described in subsection 3.3.1, where the aims of the research project were described to the schools and teachers. There were fifty-one (twenty-three female, twenty-eight male) participants, of mixed ability learners from 3 schools. The learners were aged between 11 and 12 and all in year 7. In accordance with the ethics procedure, informed consent was obtained in writing from the parents and the children participating in the study as outlined in subsection 8.1.2. [redacted] There was a roughly equal gender balance and ratio of learners from each school across the conditions.

Procedure

The teachers were emailed the learning activity in advance. Prior to the session with the robot the teachers were asked to allow all of the learners in the class to take part in the activity. The learners that wanted to participate were given consent forms and information sheets to take home for parents to approve. On the day of the study the learners were sent in one at a time to the room in which the study took place. The author began by introducing the activity to the learner. The learner then carried out the learning session with one of the conditions. Each session with a learner was 4 minutes in duration. After the learning session the learner was given the questionnaire to complete. This procedure is shown in Table 3.7.

Table 3.7: Procedure detail for study 3: embodied OLM study

Activity	Notes
Teacher briefing	Teacher given time to review the learning activity
Learner briefing	Learners in class given consent forms and information for parents to approve
Research introduces activity to learner	Researcher introduces activity to learner and shows the learner the activity and the tools
Learning session	Robot supports the learner as they take part in the activity for 4 minutes
Questionnaire	The learner completes the questionnaire to provide feedback of their experience and on the activity

Experimental setup

The study was conducted in a meeting room in the learner's school. The learners interact with the learning task individually on a touchscreen table. The task runs on a 27 inch touchscreen laid flat on a desk. The learners were standing up to enable them to comfortably reach all areas of the touchscreen. The robotic tutor was an Aldebaran Robotics NAO torso and was fully autonomous during the activity. The robot (in the conditions in which it was present) was positioned on a stand opposite the touchscreen in order for it to be at a similar height to the learner. There were two cameras (one capturing the overall situation and one focusing on the learners' faces). The arrangement of materials is shown in Figure 3.6.

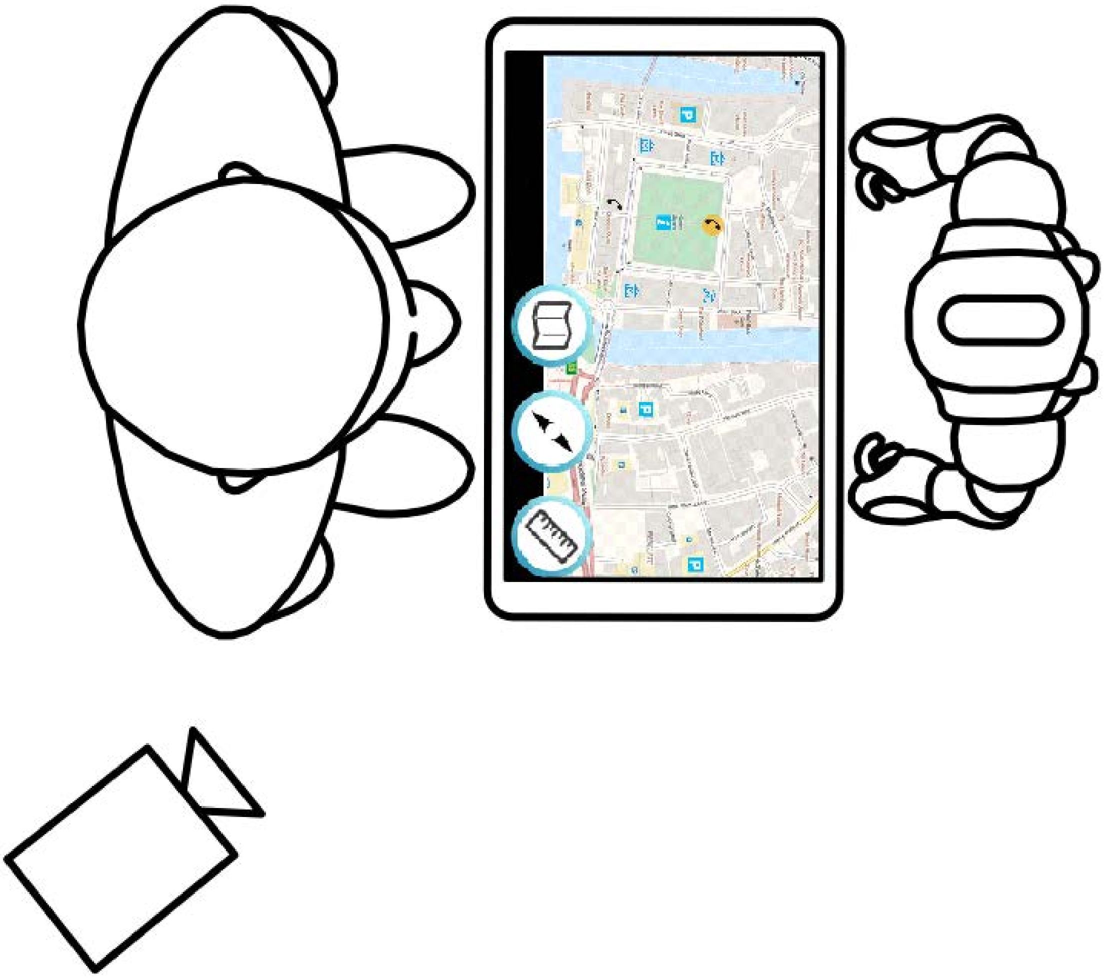

Figure 3.6: Setup study 3: embodied OLM study

Learning task

The learners are asked to carry out a simple geography object placement activity. The activity is designed to test *compass reading*, *map symbol knowledge*, and *distance measuring* competencies. The content conforms to the England and Wales National Curriculum for Geography (DfE, 2014). Previous mock-up studies described in section 3.5 with both teachers and students identified that the level of difficulty in the activity is appropriate for the learners. This activity is used as the basis for the more open-ended learning task described in section 4.2.

The activity comprises of a number of steps where the user is asked to place a map symbol on a map a certain distance and direction from the start point; this tests all three competencies that are modelled. The questions are in the form of: *"Drag the campsite symbol to the point 100m north of the star".* After each step in the activity the learner is presented with the current skill levels for each competency and a short explanation of why the skill level is at that level and what has been answered correctly and/or incorrectly. The system also delivers a brief explanation of why the skill level is at that current level, as this provides more aspects of feedback to investigate. The explanations are also summarised where possible to reduce repetition if all of the skills have changed in the same way. 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, and display a compass onscreen.

Learner model

The construction of the underlying learner model is critical. One of the main approaches to skill modelling is *Constraint Based Modelling* (CBM) (Desmarais and Baker, 2012; Woolf, 2009, 2010). CBM is a technique that can be used to model a learner's domain knowledge and skill. It does so by checking a learner's answers against a set of relevant constraints; if an answer does not violate a constraint then that answer is correct (Mitrovic, 2010). Using this approach a basic learner model containing the competencies *compass reading*, *map symbol knowledge*, and *distance measuring* is built. The model records a history and provides a basic indication of the current skill levels calculated using a weighted average so that more up to date information is more relevant than old information. The time taken to answer a question also affects the update of the learner model.

Conditions

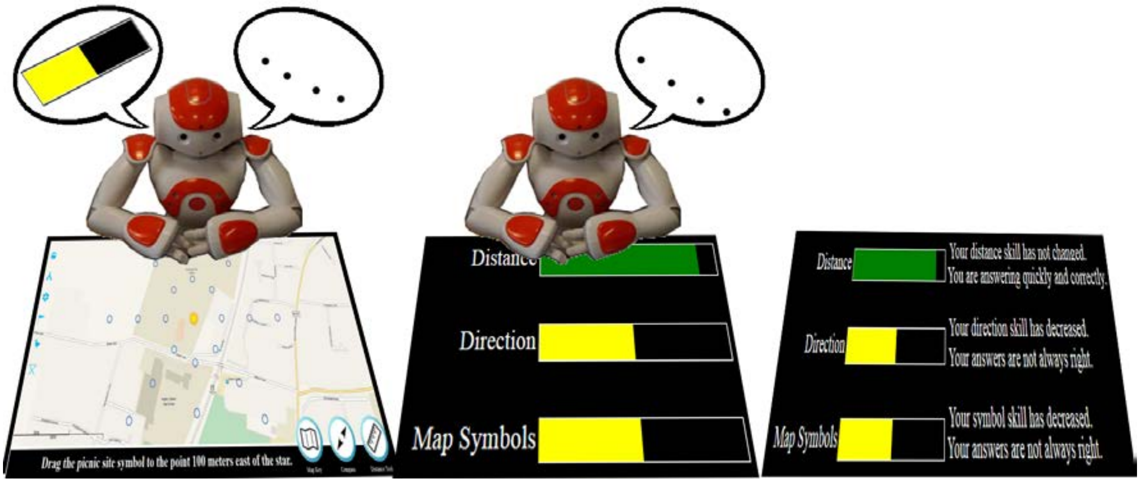

Figure 3.7: Conditions for study 3: embodied OLM study: (1) Full embodiment, (2) Mixed embodiment, (3) No embodiment

The learner is provided with regular updates on the level of their map reading skills and a simple explanation of why the skill level is at its current level.

- **Full embodiment:** Verbal communication of both the skill levels and explanation by the robot. There is no visual representation of the skill meter onscreen, the skill levels and explanation of the skill level is spoken solely by the robot. The robot makes idle motions throughout.
- **Mixed embodiment:** Skill meter onscreen with verbal communication of the explanation of skill level by the robot. Each competency is displayed onscreen

as a skill meter and the robot provides the explanation. There is no on-screen explanation and the robot does not say the skill levels. The robot makes idle motions throughout.

- **No embodiment:** Skill meters and text to present explanation onscreen. No robot is present in this condition. The skill meters are displayed onscreen with a text explanation to the side. If the explanation is the same, the text is summarised in one piece of text. The text is the same as the robotic explanation.

After each step in the activity the learner was presented with the skill level for each competency and an explanation of why the skill level was at that level. This is communicated via a pop-up onscreen or via verbal communication from the robot. All three of the conditions provide the same information and explanation, however each condition varies the way the information is presented. There are five skill levels for each competency ranging from very low, low, okay, good, and very good. The learner was informed of their skill level followed by how that level had changed since the last step; increased, decreased, or stayed the same. This was then followed by an explanation. There are just three explanations given. If the competency has increased due to a quick answer or stayed the same due to the maximum skill level being reached the explanation is "You are answering quickly and correctly". If the competency increases or stayed the same based on an answer that is correct but not quick the explanation is "You are answering correctly but sometimes a bit slowly". If the competency decreases due to an incorrect answer or has stayed the same due to the lowest skill level the explanation is "Your answers are not always right". If all competencies have updated in the same manner the explanation is summarised rather than explained multiple times. This saves time and avoids repetition.

Data collection

The primary form of data collection is a self-report questionnaire containing questions designed to elicit the learner's perceived skill level, enjoyment, engagement, perception, understanding, and trust in the learner model and system. Video, audio, task and performance data is also recorded. The questionnaire is divided into three sections of Likert style questions: 1) *'Enjoyment'*, including "I enjoyed the overall experience" and "I enjoyed the explanation of how and why my skills changed"; 2) *'Perception/Understanding'*, including "I noticed that the system understood my skill levels"; and 3) *'Trust'*, including "I trust the explanation of why my skill levels are changing". The full list of questions is in section 8.4.

3.6.3 Results

Data Analysis

Responses to the Likert scale questions were grouped in to *'Enjoyment'*, *'Perception/ Understanding'* and *'Trust'*. The reliability of these groupings was assessed using Cronbach's alpha. The mean values of each group and the individual items were analysed by comparing each condition against each other using a Mann-Whitney U test. The significant values (lower than 0.05) were then further investigated. The video recordings were reviewed to see if the users had any usability issues or difficulty interacting with the learning task, which is discussed in the summary and conclusions.

Questionnaire Results Table

Table 3.8: Embodied OLM results table

Question	Mean values						Mann-Whitney U Test					
	Mixed		None		Full		Mixed vs None		Full vs None		Full vs Mixed	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	U	p	U	p	U	p
Enjoyment												
Combined	4.52	0.33	4.05	0.66	4.46	0.44	80.0	0.026	89.5	0.057	137.5	0.812
I enjoyed the overall experience	4.82	0.39	4.18	1.01	4.71	0.47	82.0	0.031	97.0	0.106	127.5	0.563
I enjoyed doing the activity	4.76	0.44	4.24	0.75	4.71	0.47	87.5	0.049	94.5	0.085	136.0	0.786
I enjoyed being shown my skill levels throughout the activity	4.59	0.51	4.24	0.97	4.65	0.49	115.5	0.322	107.5	0.205	136.0	0.786
I enjoyed the explanation of how and why my skills changed	4.47	0.51	3.88	0.70	4.59	0.62	79.5	0.024	68.5	0.008	123.5	0.474
I lost track of time while doing the activity	3.75	1.06	3.81	1.22	3.76	1.03	120.0	0.780	128.0	0.790	135.0	0.986
I would like to play the activity again	4.71	0.59	4.00	1.10	4.35	0.70	79.5	0.041	114.0	0.444	102.5	0.150
Perception/Understanding												
Combined	4.65	0.28	4.13	0.63	4.41	0.47	67.0	0.007	107.5	0.205	102.0	0.150
I noticed that the system understood my skill levels	4.71	0.47	3.82	0.95	4.47	0.51	58.0	0.002	84.0	0.038	110.5	0.245
I noticed that the system showed me my skill levels	4.76	0.44	4.18	0.73	4.35	0.61	79.0	0.024	126.5	0.540	91.5	0.067
I noticed that the system explained why my skill levels were changing	4.59	0.51	4.18	0.73	4.53	0.62	100.0	0.131	105.5	0.182	141.0	0.919
I understood when the system showed me my skill levels	4.53	0.51	4.29	1.05	4.29	0.59	136.5	0.786	126.5	0.540	115.0	0.322
I understood the explanation of why my skill levels were changing	4.65	0.61	4.18	0.73	4.41	0.62	91.5	0.067	119.5	0.394	112.5	0.274
Trust												
Combined	4.43	0.42	4.18	0.67	4.22	0.51	112.5	0.274	143.5	0.973	108.0	0.218
I trust that the system can gauge my skill levels correctly	4.29	0.69	4.06	0.97	4.18	0.64	128.5	0.586	143.5	0.973	129.5	0.610
I trust that the skill levels shown by the system were accurate	4.18	0.64	4.29	0.59	4.24	0.56	131.0	0.658	136.5	0.786	138.5	0.838
I trust the explanation of why my skill levels were changing	4.82	0.39	4.25	0.86	4.24	0.75	80.5	0.045	130.5	0.845	80.5	0.026

Enjoyment

The Cronbach's Alpha for the grouping of *'Enjoyment'* questions was 0.76. Between the *mixed embodiment* and *no embodiment* conditions the overall enjoyment is significantly higher in favour of the mixed condition (U = 80; p= 0.026). At an individual level this was due to these questions having significantly higher values in the mixed condition: "I enjoyed the overall experience" (U = 82; p=0.031423), "I enjoyed doing the activity" (U=87.5, p = 0.048686), "I enjoyed the explanation of how and why my skills changed" (U=79.5; p=0.023766), "I would like to play the activity again" (U=79.5; 0.040674). When comparing the *full embodiment* and *no embodiment* conditions, overall, there were no significant difference, however the following question had a significantly higher result for full embodiment: "I enjoyed the explanation of how and why my skills changed" (U=68.5; p =0.007611); There were generally higher values across the other questions but not to a significant level. Between the *mixed embodiment* and *full embodiment* there were no significant differences. Across all conditions the following question showed no significant difference: "I enjoyed being shown my skill levels throughout the activity". It appears that embodiment played a limited role in the showing of skill levels but had more significance in the explanation.

Perception/understanding of the model

The Cronbach's Alpha for the grouping of *'Perception/Understanding'* questions was 0.79. In the *mixed embodiment* vs *no embodiment* conditions the overall perception of skill meters and explanation was greater with the mixed condition to a significant degree (U=67; p=0.007). This can be seen at an individual level with the following questions being higher for the robot condition by a significant amount: "I noticed that the system understood my skill levels" (U= 58; p= 0.002269), "I noticed that the system showed my skill levels" (U= 79; p= 0.023766). "I understood the explanation of why my skill levels were changing" were higher but not significantly so.

When comparing the *full embodiment* and *no embodiment* conditions there was no overall significant difference, however the following question had a significant higher result: "I noticed that the system understood my skill levels" (U=84; p =0.037590). Other values again were higher but not significantly. Between the *mixed embodiment* and *full embodiment* there were no significant differences.

Trust in the model

The Cronbach's Alpha for the grouping of *'Trust'* questions was 0.615, which is a rather low value. Overall there were no significant differences between any of the conditions. A more detailed review reveals no significant differences with respect to questions concerning the building of the model: "I trust that the system can gauge my skill levels correctly" and "I trust that the skill levels shown by the system were accurate". However, there were some significant differences with the following question: "I trust the explanation of why my skill levels are changing". In the *mixed embodiment* vs *no embodiment* conditions the value is higher in the mixed condition (U=80.5;p=0.044523). The *full embodiment* condition is higher than the *no embodiment* condition but not to a significant degree for the same question. The *mixed condition* leads to higher values than the *fully embodied* condition (U=80.5; p=0.026122).

3.6.4 Discussion

From these results it appears that embodiment has the largest effect in the explanation of the model. There is greater enjoyment with some amount of embodiment, there is greater perception that the system understands the learner, and there is more trust in the explanation.

The embodiment has less of an effect in respect of the perception of skill meters. This may be because the skill level is quite a simple concept to understand. The perception of skill levels changing and understanding that skills were changing was the same across all conditions. This was to be expected as this was made obvious in the experimental design.

There was general consensus that the type of feedback provided, the skill meter and explanation were liked and understood across all conditions, which was encouraging for continued use of this feedback.

Limitations

One limitation of this study is the absence of a comparison to a virtual embodiment. Such a comparison will enable analysis to explore if and to what extent the physical presence was responsible for the above results as opposed to other factors, such as the feedback being in a different medium.

A further limitation concerned the skill meters. As they were not on the screen at all times this may have limited their use. However, limiting skill meters to a pop up allowed a closer comparison to robotic speech which cannot be present all of the time.

3.6.5 Summary and conclusions

The findings suggest that a robotic embodiment interacting with the screen can increase enjoyment, understanding, and trust in explanations of an OLM. The results show promise for the introduction of a physical embodiment when providing feedback concerning skill levels, however to gain the most advantage the robot should be used to explain and elaborate rather than simply state skill levels. The robot and OLM combined appear to be a very effective way to have a learner reflect on their developing skills. That there is trust in the explanation is very encouraging as this means that the learner may pay attention and act based on the explanation.

These findings are used to inform the design of the robotic tutor and the OLM detailed in chapter 4. Specifically the robot and learner will be able to make use of an OLM that is always visible to a learner at the edge of the screen. The robot will be able to use the OLM to highlight and further explain the learner's developing skills. This study is also important formative feedback for the development of the learning task as this is the first time the learners have used an electronic version of the learning task. Observations of how the learners interacted with the task feed into further development of the task to make it more user friendly and easier to interact with, e.g. making the distance tool easier to use.

This study was a short-term study and did not seek to investigate SRL as a whole so the activity was quite simple. For this reason it was relatively easy for some students to master the activity in the time available. In future development it is required that the learning task should be open-ended and more difficult to allow learners to demonstrate and develop SRL skills.

3.7 Study 4: UCD teacher study

3.7.1 Introduction

This study investigates teacher scaffolding to support reflection and SRL with an OLM, in a geography based task on a touchscreen table. This UCD study was used to elicit requirements, and create a specification to inform the design of the robotic tutor. The study was carried out in 6 one-on-one sessions with students between the ages of 10 and 11. Examples of teachers scaffolding students' SRL behaviours using the OLM are presented, based within the learning scenario where learners are able to demonstrate independent learning and SRL skills, demonstrating how an OLM can be used to prompt the learner to monitor their developing skills, set goals, and use appropriate tools. The learners also have access to an OLM that may be able to help them to reflect on their knowledge and developing skills. How teachers co-regulate a learner's SRL skills to learn effectively in this learning scenario is investigated. The interaction is annotated based on the relevant literature and theory and this is used as a basis to develop a computational model to support SRL skills and also as a base to develop behaviours for a robot tutor to support SRL skills.

Motivation

As previously discussed, 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 (Zimmerman, 2008). OLM externalise the model that the system has of the learner in a way that is interpretable by the learner or teacher. The aims of OLM include promoting reflection to facilitate planning and decision-making, and raise awareness of understanding or developing skills (Bull and Kay, 2013).

Previous research has highlighted the importance teachers have in respect of support for reflective processes (Reingold et al., 2008). Research indicates adaptive or personalised scaffolding of SRL approaches by teachers leads to a greater adoption of SRL skills as compared to conditions where no scaffolding was offered (Azevedo et al., 2011). As a meta-cognitive interaction observed in a laboratory may not be valid in a school environment (Koedinger et al., 2009), a UCD approach is employed at the student's school as this allows an investigation in to how these skills can be scaffolded in a more realistic environment. It is recommended that research is conducted to understand the complex nature of learning mechanisms that may facilitate learning within these environments (Azevedo, 2005).

Previous work has shown that teachers' behaviours can be modelled to develop tactics and strategies for tutoring systems (Du Boulay and Luckin, 2016; Olney et al., 2012; D'Mello et al., 2010; Lehman et al., 2012; Lepper and Woolverton, 2002; Person and Graesser, 2003). The reason for this is that human tutors are seen as the gold standard for learning (Lehman et al., 2012). This UCD teacher study investigates how teachers' behaviours that support the development of SRL skills in learners can be modelled.

Research questions

The research questions to be answered in this study are:

- How would experienced teachers use the OLM and learning task to support SRL skills?
- How do teachers engage and motivate students to engage in SRL learning skills?
- What do good and poor SRL behaviours look like in this domain?

3.7.2 Method

The goal is to develop a computational model and a robotic tutor that can scaffold SRL via an OLM. To this end, this UCD study aims to elicit how teachers personalise feedback using an OLM to scaffold reflection and SRL. The aim of this study is to identify how teachers use an OLM to scaffold reflection and SRL in teaching a student. This is a qualitative study with a thematic analysis.

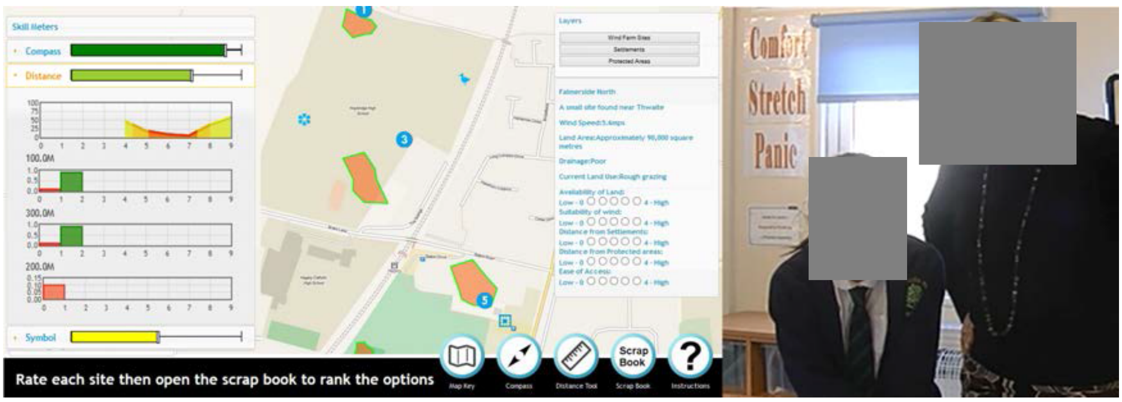

Figure 3.8: OLM, learning task, learner and teacher for study 4: UCD teacher study

A map based learning scenario that enables the learner to exhibit SRL skills and processes has been developed, i.e. self-monitoring, goal setting, and help seeking. The learner has a choice of activities of varying difficulty that allow them to practice map reading skills for distance, direction, and map symbols. This includes the *Cardinal Directions*, *Inter-cardinal Directions*, *Distance in Metres*, *Distance in Kilometres*, *Map Symbols*, *All map skills*, and *Art trail* activities described in section 4.2. The learner and teacher also have access to tools which can help with the activity. A learner model of the student's map reading competencies is built using constraint based modelling. The OLM shows skill meters for each competency from the learner model 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. The learner and teacher can inspect a history of the most recent 10 pieces of evidence for each individual competency by clicking on the corresponding skill meter. This OLM enables both the learner and teacher to see exactly in which aspect of the competency their strengths and weaknesses lie. The details of all of these elements are described in detail in section 4.4.3.

The teachers were requested to act in a way to support SRL of the learner. The interactions were then analysed to see how the teachers support SRL skills.

Participants

Schools and teachers were approached and recruited as described in subsection 3.3.1. Expert teachers were requested to assist individual learners in the learning activity. This study involves 3 teachers and 6 students, with each teacher assisting 2 students individually through the activity, resulting in 6 sessions in total. The teachers were asked to select six students of different ability to increase the chance of observing different teaching styles. The students are between the ages of 10 and 11 and of mixed sex and ability. The details of the participant are shown in Table 3.9. In accordance with the ethics procedure, informed consent was obtained in writing from the teachers, parents, and the children participating in the study as outlined in subsection 8.1.2. [redacted]

Table 3.9: Participant details for study 4: UCD teacher study. Session. Teacher gender, age, teaching experience, and current position. Learner gender, age

Session	Gender	Age	Teaching Experience	Position	Learner Gender	Age
1	F	62	40	Head of phase	F	11
2					M	10
3	F	57	12	Head of English	F	10
4					M	11
5	F	57	25	Teaching assistant and special education needs coordinator	F	11
6					M	11

Procedure

The teachers were emailed the learning activity in advance. The learners that were selected by the teachers to participate were given consent forms and information sheets to take home for parents to approve. On the day of the study prior to the session the teachers were given an introduction to the task and the OLM. The teachers were asked to provide assistance using the OLM where possible but to also focus on helping the student acquire SRL skills and to avoid giving direct answers. On the day of the study the learners were sent in one at a time to the room in which the study took place. The students were asked by the teacher to use the learning task to practice and develop their map reading skills. They were informed that they were in charge of their own learning and could choose the order of the activities and how long they wanted to do any activity for. This is similar to the adaptive content and process scaffolding (ACPS) (Azevedo et al., 2011), where students are provided with adaptive content scaffolding (domain support) to ensure they are meeting the overall learning goal and adaptive process scaffolding (SRL support) and are using the key self-regulatory processes, such as reflection, planning, and using the tools available in the activity. The sessions were as long as required by the learner; between 15 and 30 minutes in length. This procedure is shown in Table 3.10.

Table 3.10: Procedure detail for study 4: UCD teacher study

Activity	Notes
Teacher briefing	Teacher given time to review the learning activity
Learner briefing	Teacher selected participants, consent forms and information sent to learners parents to approve
Teacher introduces activity to learner	Teacher introduces activity to learner and shows the learner the activity and the tools
Learning session	Teacher supports the learner as they use the learning activity

Experimental setup

The study took place in a classroom in the teachers' and learners' school. The learners interact with the learning task individually on a touchscreen table. The task runs on a 27 inch touchscreen laid flat on a desk. The learners were standing up to enable them to comfortably reach all areas of the touchscreen. The teachers were standing to the left of the learner. Two cameras (one capturing the overall situation and one focusing on the participants' faces). The arrangement of materials is shown in Figure 3.9.

Data collection

Audio and video recordings were made by the researcher. Two cameras were used as described above. The task recorded all interactions with the touchscreen to a log file and database.

Figure 3.9: Setup study 4: UCD teacher study

3.7.3 Results

Video and task logs were reviewed and coded by a single coder using the coding scheme described below. The analysis focused on how teachers used the OLM to scaffold SRL skills and processes detailed in the *OLM and SRL phase analysis* section below. However, the interaction was also analysed at a broader level taking into account dialogue and all interactions within the activity to see how teachers motivated and supported the students throughout the whole interaction, this is detailed in the *Dialogue dimension and instructional scaffolding coding* section below.

Data Analysis

The video and audio recordings were transcribed and reviewed by the author. The transcription of the video was supported with the ELAN software (Wittenburg et al., 2006). ELAN allows the analysis of a video and audio and allows the researcher to record event details, along with start and end times, into a file. The details from the events from ELAN files were placed into a spreadsheet. This included all of the speech, gestures, and non-verbal behaviours of the teachers and learners.

The events in the task log were extracted and synchronised with the timings of the events recorded using ELAN. The task events were also placed into the spreadsheet so that they could be compared with the events from the video and audio recordings. This included the details of the questions answered, the interaction with the tools and the OLM.

One spreadsheet was created for each session. Each event was placed on its own row so there existed a time-line over the session containing all of the teacher, learner, and task events. Columns to the right of the event could then be used to record the coding detailed in the sections below. An example of the time-line of learner, teacher, and task events with coding columns is shown in Table 3.11.

Table 3.11: Study 4: UCD teacher study: example time-line of learner, teacher, and task events with coding columns

Start	End	Duration	Text	Source	Actor	Action	SRL Phase	SRL Subprocess
15:44.5	15:46.5	00:01.9	Where is the English heritage site?	Elan	teacher	Question Directed-Activity	Performance	Self control - task strategies
15:46.4	15:47.2	00:00.8	Here	Elan	learner	Complete verbal contribution		
15:46.9	15:48.6	00:01.6	Half a KM is how many meters?	Elan	teacher	Question Directed-Activity	Performance	Self control - task strategies
15:48.7	15:49.9	00:01.2	500 meters	Elan	learner	Complete verbal contribution		
15:54.0				Task	learner	Correct answer		

OLM and SRL phase analysis

The coding scheme is based on Zimmerman's SRL phase and sub-process (Zimmerman, 2008). The diagram from Zimmerman is reproduced in Figure 3.10. This model is also similar to the principle sub-functions from Bandura (Bandura, 1991); self-monitoring, judgement, and affective self-reaction.

Figure 3.10: Zimmerman's cyclical SRL model: phases and sub-processes of self-regulated learning

The results revealed that the teachers used the OLM to scaffold the following SRL processes:

- **Self-reflection phase.** The teachers use the OLM to prompt the learners to reflect in a number of ways, including prompting the learner to self-evaluate and attribute causes for the changes in the model of their developing skills: “What is that showing us then?” and “It is good because you got everything right, what do you think would happen if you got something wrong?”. The teachers also show satisfaction as the competencies increase: “Oh well done! It has shot right back up again now!”.

- **Forethought phase.** The teachers then build upon the learner’s awareness of their developing skills to help set goals and strategies. When the OLM is showing that the student has a high level of competency the teachers use the OLM to suggest moving on to a new activity: “I think you are pretty good at that, do you? So what about the inter-cardinal directions?” and “look at that! Now, do you think that was a bit easy for you? Do you want to try out some of the others?”. If the student has not mastered a skill the teacher will suggest continuing the activity until they have: “This is really good, but this is wrong (referring to one element of the OLM), let’s continue it so that we can get 100%”.

- **Performance phase.** The teacher also used the OLM as a basis for task strategies. If the learner is being overly cautious and double checking each answer with a tool the teacher will encourage them to be more confident and efficient: “Oh that’s it, you are on a roll now (indicating OLM increase), you might not need to use the tool any more, you might have worked it out, what do you think?”. When there is an issue with the learner’s understanding, the OLM was used to highlight this: “Oh what happened to the meter, did you get that one right?” *”I think I went west.”* ”Yeah, you can see here that the last attempt at east was wrong”, the learner then proceeds to use the compass tool. Another example: “Why has it gone dark? That’s interesting, what do you think that tells you there?” *”That I got it wrong”*, the learner then proceeds to use the map key to identify the correct symbol.

Interaction analysis for OLM use The interaction between the teacher and learner has been analysed, with the aim of understanding how and why the teacher uses the OLM in reaction to learner actions. A similar approach to the Turn Transition Matrix (TTM) analysis has been used, which is used to identify dialogue patterns (Person and Graesser, 2003). Video analysis combined with application logs was used to create a TTM that shows what a teacher does with the OLM in response to a learner action. The matrix is presented in Table 3.12. It was observed that teachers try to encourage the use of the OLM for its intended purpose of reflecting on developing skills.

When a learner is correctly answering, the teachers are prompting the learner to be aware of increasing skill levels by simply directing attention to the OLM (13 times), or by discussing the OLM at a high level (9 times), or by specifically inspecting (7 times) and discussing it in more detail (7 times). Similarly when there is an incorrect answer the teachers direct attention to the OLM (5 times) and they will discuss the OLM at a high level (6 times), however they appear to focus less on specifics as they only specifically inspect elements (2 times) and discuss in more detail (3 times). This is likely due to the learners getting more answers correct than incorrect; see Table 3.14. It could also be due to the teachers offering other reflective or domain support that does not involve the OLM; see Table 3.13.

The above analysis shows that the teachers really want to make the learner aware of their developing skills and they are able to make use of the OLM as a tool to do this. Even when a learner is answering correctly they can use the OLM as a tool to prompt the learner to plan and move on to more difficult tasks. Additionally the OLM is another tool that can be used to motivate students by showing them the results of their efforts. These different behaviours are now analysed further in the following sections.

Table 3.12: Study 4: UCD teacher study: Turn Transition Matrix - the matrix records the interaction between the teacher and learner, specifically what a teacher does with the OLM in response to a learner action

Learner action	Introduce OLM	Directs attention to OLM	Look at high level OLM	Discuss OLM High Level	Inspect OLM	Discuss OLM Low Level	Question OLM Contents
Correct answer	1	13	2	9	7	7	0
Partially correct answer	0	2	0	2	2	0	0
Incorrect answer	0	5	0	6	2	3	1
Tool use	0	1	0	0	0	0	0
Look at high level OLM	0	0	0	1	0	0	0
Discuss OLM High Level	0	0	0	3	0	1	0
Inspect OLM	0	1	0	5	8	21	1
Discuss OLM Low Level	0	0	0	0	0	1	0
Complete verbal contribution	2	1	0	1	0	0	0
Acknowledgement	0	1	0	0	1	1	0
Confirmation	0	2	0	0	1	2	0

Dialogue dimension and instructional scaffolding coding

In addition to the use of the OLM, teachers and learners general behaviours have been coded to look for further interaction patterns that are not only reliant on the use of the OLM. The coding scheme for the learners and teachers was based on a number of studies that look at the dialogue dimensions (Reingold et al., 2008; Person and Graesser, 2003; Wagster et al., 2007b; Alves-Oliveira et al., 2014; Graesser et al., 1999; Hattie and Timperley, 2007; Deci et al., 1991) and instructional scaffolding (Meyer and Turner, 2002) that occur in education. The coding categories for dialogue and behaviours are: support for SRL process; high level feedback; domain support; and other. In Table 3.13 the counts of each item from the coding scheme that the teachers performed are shown. In Table 3.14 the counts of each item that the learners performed are shown.

Teacher coding The gaze, behaviour and dialogue of the teachers were annotated them against the coding scheme. Support for SRL was considered, not just using the OLM as was done in the above section, but throughout all dialogue and interaction with the system. The support for SRL process have been broken down into Zimmerman's SRL phases. The counts of the teachers actions are presented in Table 3.13 and discussed below.

- **SRL self-reflection phase.** As in the above section support for the self-reflection phase can fall into the further sub-category of self-judgement or self-evaluation (Wagster et al., 2007b). Support for this phase is observed when the teacher introduces or highlights the OLM at a high or low level as above. There are multiple times when the teacher asks questions aimed to support self-evaluation or reflection (Person and Graesser, 2003) when the OLM is not used: "Okay, now, do you think that was a bit easy for you?" or "How are your compass skills do you think?". The teachers are also concerned with helping the students regulate their emotions (Meyer and Turner, 2002) and motivating the students: “How do you feel? This is really good isn’t it?”.

- **SRL forethought phase.** As in the above section the teachers support the learners in the forethought phase. This is where the teacher supports high level task strategies. The teachers make it clear that the learner is in control and they are in charge of the learning: “Which would you like to start; you can do anything you fancy”, ”What activity should we do now, because you have the choice of different ones” or “I don’t know!” to prompt the learner to set their own goals. However, the teachers will prompt the learner to make a choice if they are not testing themselves: “I think you have got the hang of that one, so move on to the all map skills activity”. This is a good example of co-regulation and may also prompt the learner to reflect on their skills levels. The teacher tries to encourage the student by supplying mastery goals to prompt the learner to continue: “Let’s do it so that we can get 100%”. At other times the teacher does not focus on achieving mastery but encourages practising: “It doesn’t matter if you don’t get things correct, because then we will see where we can perhaps improve your scores.” These are the different approaches that the teacher employs to keep the student motivated at this goal setting level. The teacher also supports motivation by trying to prompt self-motivation beliefs in line with self-determination (Deci et al., 1991) and tries to highlight the intrinsic value and interest of the task (Meyer and Turner, 2002).

- **SRL performance phase.** This is where the teacher provides support for self-control and various different task strategies. The teacher will offer SRL support at a lower level and try to assist with the strategies that the learner should use to solve the problems in the task, e.g. ”Look you can bring the compass up, that can remind you about the directions”. Or they may even suggest some trial and error and self-monitoring: "You can just give it a try and see what happens to the skill meter". The teacher also gives examples of how they would go about the activity: "Never eat shredded wheat, what do you do?", "I probably would to remind me what they are". A large part of the tutoring is to instil self-control and focus the attention of the learner to the task. To do this the teacher will highlight keywords (Anghileri, 2006), and make summaries of the question (Graesser et al., 1999). This can take the form of asking a lot of questions in order to redirect a student's efforts (Person and Graesser, 2003) e.g. "okay, so where is the scrap book?"

- **High level feedback**. Outside of the specific SRL support the teachers provide a lot of motivational support through positive feedback both verbally and with nods of encouragement. The teachers give very little negative feedback; this is similar to findings by Person (Person and Graesser, 2003), rather the teacher will give more sympathetic encouraging feedback and say things like "that is almost right".

- **Domain support**. The teacher gives specific domain support and directives for the learner to perform a specific action in the task. This support is primarily given to explain a concept, task, or tool the first time a learner encounters it. If the learner takes some time to provide an answer then the teacher will start asking questions to prompt the learner to answer. The teacher sometimes helps with technical support if the learner has not touched the touchscreen table properly or needs assistance with a tool.

- **Other support**. The other support that is given by the teacher is for text comprehension; this is to help learners when they are reading out loud unfamiliar words. The teacher may also sometimes make some social comments (Alves-Oliveira et al., 2014), however social comments are infrequent and the teachers are very professional once the activity has begun.

Table 3.13: Study 4: UCD teacher study: teacher coding table - dialogue and behaviours are coded into four action categories

Action	SRL Phase	Sub-process	Count
Support for SRL process			
Discussion with OLM	Self-reflection	Self-judgement - self-evaluation	99
Question to prompt reflection	Self-reflection	Self-judgement - self-evaluation	25
Affect regulation	Self-reflection	Self-reaction - self-satisfaction/affect	6
High level strategy	Forethought	Task analysis - strategic planning	33
Presenting rational for task and activities	Forethought	Self-motivation beliefs - task interest/value	25
Task Strategy	Performance	Self-control - task strategies	64
Keyword	Performance	Self-control - attention focusing	40
Task step	Performance	Self-control - attention focusing	30
Student ability	Performance	Self-judgement - self-evaluation	11
Question Leading	Performance	Self-control - task strategies	5
High level feedback			
Positive Feedback			98
Neutral Feedback			11
Almost Feedback			4
Domain support			
Question Directed-Activity			80
Directive			51
Explanation of task			33
Explanation of tool			29
Hint			21
Technical support			17
Explanation of concept			11
Question Pump			11
Other			
Supervising text comprehension			12
Social			3

Learner coding The task actions, gaze, behaviour and dialogue of the learners was recorded and annotated them against the coding scheme. All behaviours were included, not just the actions of using the OLM, as was done in the above section. The behaviours regarding SRL processes have been broken down into Zimmerman's SRL phases. The results are presented in Table 3.14 and discussed below.

- **SRL self-reflection phase.** The learner frequently inspect the OLM, however the learner does not discuss the contents very frequently. The learners appear to be aware of the OLM even when not inspecting it, as the learner comments on the OLM when they think it does not match their skills, e.g. due to a sleeve interfering with the screen causing an incorrect answer: "look it has gone wrong again (pointing at OLM)!".

- **SRL forethought phase.** Unfortunately the activity does not allow many ways to observe the learner's forethought. The main indicator of forethought in the activity is when the learners choose the activity, however this is often prompted by the teacher.

- **SRL performance phase.** The learners display many behaviours that are not observable by the system. This includes seeking confirmation or help from the teacher, reading out loud to focus attention, or thinking out loud while solving problems. Although it is observed that learners make use of the tools to solve the problems, this use is lessened because they are able to rely upon the teacher for help.

- **Task actions**. The remaining task actions are giving correct and incorrect answers, there are far more correct answers given than incorrect answers.

- **Other**. The other actions include verbal contributions in discussions with the teacher, or non-verbal acknowledgements of the teachers scaffolding.

Table 3.14: Study 4: UCD teacher study: learner coding table - dialogue and behaviours are coded into three action categories

Action	SRL Phase	Sub-process	Count
SRL process			
Inspect OLM	Self-reflection	Self-judgement - self-evaluation	41
Discuss OLM	Self-reflection	Self-judgement - self-evaluation	8
High level strategy choosing activity	Forethought	Task analysis - strategic planning	30
Help seeking from teacher Request confirmation	Performance	Self-control - task strategies	19
Tool use	Performance	Self-control - task strategies	8
Reading out loud	Performance	Self-control - attention focusing	21
Think aloud	Performance	Self-control - self-instruction	19
Task actions			
Correct answer			219
Incorrect answer			61
Other			
Verbal contribution			53
Acknowledgement of teacher			8

3.7.4 Discussion

This study indicates that scaffolding students' SRL behaviours using the OLM can be used to produce an environment in which students experience greater learning gains through developing their SRL processes. From this study it has been identified how teachers use the OLM to demonstrate reflection and SRL learning techniques. The teachers do this 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. The aim is to use these findings as a basis for developing robot interactions.

Previous studies have suggested that prompts used to highlight errors to encourage self-reflection and reasoning can be effective in leading the learner to self-correct those errors (Bull and Kay, 2013; Koedinger et al., 2009). In addition, prompting reflection on skill levels can lead to improved problem selection (Mitrovic, 2010). These are the prompts that the teachers were observed using with the OLM to scaffold SRL behaviours. Interestingly the teachers use the OLM frequently when the learners answer correctly. In this context, it is used as a tool to prompt the learner to plan and move on to more difficult tasks, this indicates that teachers are making use of the OLM to motivate and show the learner how their efforts are leading to an increase in skill.

Limitations

This study was somewhat limited due to the small number of participants and short duration of the activity and the fact that there was only one coder available to code and annotate the interaction.

Unfortunately some of the SRL behaviours the learner performs are not observable by an autonomous system. This includes the learner seeking confirmation or help from the teacher, reading out loud to focus attention, or thinking out loud while solving problems. This means that it is not possible to include these behaviours in a model of the learners SRL skills at present. However, as the sensing capabilities of robots increases it is hoped that these aspects could be included, which will certainly enhance the relationship between a robotic tutor and learner.

3.7.5 Summary and conclusions

The teachers are able to use the OLM to scaffold reflection on developing skills. This study provides a range of examples of social co-regulation of SRL skills. The teachers are trying to make it clear that the learner is in charge and should explore and experiment. However to avoid the student becoming demotivated the teachers are eager to help students if they do start to encounter difficulties. While the teachers want the learners to be in control, sometimes they may offer help too readily, with the result that a learner may not identify problems themselves or engage their SRL skills. DuBoulay (Du Boulay and Luckin, 2016) suggests that the best tutors are those that not only provide feedback efficiently but also balance this feedback with motivational support. From these examples the importance of balancing social support, SRL support and domain support is obvious.

This study is used to inform the design of the computational model of SRL that the robotic tutor can use as the basis for the SRL scaffolding. A large number of examples of SRL scaffolding with an OLM have been identified. The speech and gestures of the teachers can be used as the basis for the robotic tutor's speech and gestures. In subsection 5.2.2 the specific behaviours that have been implemented on the robot are described.

The strength of this study lies in the fact that the OLM is being used by experienced teachers and students in a natural school setting. It is very encouraging that teachers use the OLM when children are answering correctly, this shows the importance of prompting the learners to reflect on their developing skills.

Additional feedback on the activity has been provided from these interactions. Based on the high rate of correct answers it has been identified that the difficulty of the activity should be increased. Further, the learning task has been expanded due to the previously limited opportunities to show forethought by adding a *wind farm* activity, which requires planning and should test additional forethought and problem solving skills.

3.8 Summary of user-centered design

In this chapter the rationale for following a UCD approach has been set out. The iterative UCD process has been described, detailing how each design activity or study has informed and is linked to the others. The UCD studies have led to requirements that have been turned into specifications to drive the development of the tutoring system to meet the needs of the learners and teachers. At high level these studies have led to a specification for a learning scenario where a social robotic tutor aims to support the development of SRL skills using an OLM.

In this chapter it has been shown how the learners and teachers have been included at a very early stage in the design of the system with the aim of providing a system and a robotic tutor that the teachers would welcome into their classroom and their curriculum. Feedback provided here led to the specification and development of the learning scenario as a whole, including: the learning aims, the learning task, the role of the robot, and the contents and interaction with the OLM.

The findings in section 3.4 indicate that teachers would like the robot to support learners in more open-ended learning scenarios and to encourage SRL learning skills, or in their words, "independent learning skills", which include the learner reflecting on their developing skill and competencies. The teachers see the potential for an OLM or skill meters to provide feedback on learners' skills/competencies. The teachers would also be happy for a robot to take a place in the classroom.

In section 3.5 a paper prototype of the learning task was tested with the end users. A real teacher supported three individual learners through the activity as it can be difficult for teachers to explain in detail how they would adjust to different students' needs on the basis of an abstract description of the task. This has helped to refine requirements for the learning scenario and the robots role. This type of activity would be suitable for the demonstration and development of SRL skills. Teachers do want to support SRL in practice and this study has provided some ideas about how the robot might be able to achieve this. This type of activity allows for a shared space in which the embodiment of the robot could be used.

In section 3.6 the feasibility of a robot embodiment and OLM to deliver skill based feedback was explored. It was found that this feedback could be the basis of reflection and the development of SRL skills. The main recommendation being that the robot should be used to explain and elaborate rather than simply state skill levels. Furthermore, the fact that a robotic embodiment interacting with the screen can increase trust in the explanation of skill levels, is very encouraging, as this means that the learner may pay attention and act based on the explanation. This was an important study to understand the learners' user experience of this type of feedback.

In section 3.7 it was observed that teachers are able to use the OLM to scaffold reflection on developing skills. This study provides a range of examples of social co-regulation of SRL skills using the OLM. This study is used to inform the design of the computational model of SRL that the robotic tutor uses as the basis for the SRL scaffolding.

Part of the reasoning behind section 3.5, section 3.6, and section 3.7 was to explore issues with prototypes. There are benefits of prototypes in HRI research, while not as robust as finished systems, the rapid prototypes are less expensive to design and test, they enable the involvement of the users more often, and they can lead to valuable formative feedback at an early stage of system development (Šabanovic et al., 2011). The next section will describe the implementation of the learning scenario based on literature and the findings from these UCD studies.

In summary, an iterative UCD process was performed to investigate how to enable a robot to display key social and SRL scaffolding abilities. These UCD activities guided by the design goals (subsection 3.2.1) can help ensure that the competencies of the robotic tutor are implemented in an appropriate and believable manner, have real world application in the complex school environment, and meet the needs of both learners and teachers (Jones et al., 2015d).

CHAPTER 4

TUTORING SYSTEM DEVELOPMENT

This chapter describes the specification, development, and implementation of the learning scenario/tutoring system as a whole. System specifications have been created based on the requirements elicited in the literature review and UCD design studies.

This chapter aims to show how the learning task, robotic tutor, learner model, pedagogical models, and OLM are integrated into the learning scenario to support reflection and other meta-cognitive skills. A high level specification of the whole learning scenario is presented, including a high level system architecture, which describes the main modules of the system and how they interact. Following this there are detailed specifications, design, and implementation detailed for each module of the tutoring system. Building upon this technical architecture a computational approach to adaptively scaffold SRL is described in chapter 5.

4.1 High Level Architecture

This section discusses the specification and design of a learning scenario where SRL skills can be practised and developed. For SRL to occur the learning technologies need to be carefully designed to include elements to support SRL skills (Kitsantas, 2013). Based on the requirements elicited in the literature review and UCD design studies a number of system specifications have been created. The high level specifications and design are described in this section. More detailed specifications, design, and implementation details are discussed in the sections that follow.

4.1.1 Specification of the learning scenario

The high level specification is to develop a learning scenario where a social robotic tutor aims to support the development of SRL skills using an OLM.

Learner's interaction with the learning task and OLM The learner should interact with a learning task that can be used to monitor the learners progress through the activity. It is not possible to monitor the student with an camera, EEG, etc, or look at disengagement as this technology is not generally available; Additionally as this a school environment the use of a video or audio recording may not always be possible. This means that the system must sense the learner through their interaction with the learning task. The OLM should be visible to the learners at all times and the learner should be able to view updates (Long and Aleven, 2013b). The learner should also be able to inspect the OLM to get access to more detail (Mitrovic, 2007).

Learners' interaction with the robotic tutor The robotic tutor should be able to respond to the learner's actions in the activity and scaffold SRL skills via the OLM. The specification for the learner's interaction is limited by the sensing capabilities of the technology available. Ideally, the system would be able to respond to the learners' affect, speech, and actions outside of the activity however, the sensing capabilities are not available with the equipment.

The robot should be able to give verbal and non-verbal support to the learner. In addition to this the robot should be able to control aspects of the activity. The robot needs to be able to look and gesture to the learner and key areas of the learning task. This means that the robot needs to be in a position where the learner can clearly see and interact with the robotic tutor.

4.1.2 High level interaction design

With the above specifications and considerations in mind, the interaction between the tutor and the learner is mediated by a large touchscreen table. The touchscreen table provides a collaborative context where a social interaction may take place, this approach is used with social robots in the "Sand-tray" system (Baxter et al., 2012). The use of a touchscreen table avoids technical limitations with speech recognition and natural language processing and enables autonomous interaction as discussed in subsection 2.2.2; the robot is able to detect the learner's actions in the learning scenario and respond to the learner actions, i.e. positive beeps for a correct answer, sympathetic beeps for an incorrect answer, and directing its gaze to the area that the learner is interacting with.

In addition to the task, the OLM is present on the touchscreen, with which both the robot and the learner can interact. The OLM displays the learner's current skill levels in compass reading, map symbol knowledge, and distance measuring competencies. The robot is able to interact with the OLM to help the learner reflect and discuss the learner's developing competencies, which based on the findings in section 3.6 is an important aspect for supporting reflection. An example is shown in Figure 6.3. Indeed, previous research has shown that interactive touch tables with visualisations similar to OLM can be used to prompt the user to change their behaviour (Morris et al., 2006).

The robot is positioned on a stand opposite the touchscreen in order for it to be at a similar height to the learner. The position of the robot opposite the learner allows the robot to gesture to the touchscreen and the gestures be easily observed by the learner. An example is shown in Figure 6.3. Although positioning the robot

Figure 4.1: Robot highlighting OLM to a primary school student

next to the learner was considerd, as the teacher was positioned in this way in study 4 (section 3.7) and is a natural way for collaborators to be positioned. This approach was not taken as it would be harder for the learner to observe the robot, the robot may obstruct the learner, and the learner may damage the robot.

4.1.3 High level system architecture

This section describes the system architecture of the tutoring system to support the specifications and high level interaction design. The system is consistent with the main components of most intelligent tutoring systems (Bull and Kay, 2013) and has the following modules:

- Learning task interface. The learner interacts with the learning task interface on the touchscreen. The content displayed in the learning task interface is determined by scenario script and updated by the scenario manager. Further design and implementation details are presented in section 4.2.
- Scenario manager. This module or controller ties all of the other modules together. This listens for updates from the learning task and OLM interfaces

and coordinated communications between the other modules. Ultimately concluding in the learning task and OLM interfaces updating and the robotic tutor performing a behaviour. Further design and implementation details are presented in section 4.2.3.

- Scenario script. This contains information about the learning scenario as a whole; the activities available to the learner in the learning task; the details of the introduction given by the robotic tutor; and the length of the learning session. Further design and implementation details are presented in section 4.2.3.

- Scenario state. This tracks the learners' progress through the scenario script; which activity the learner is doing etc. Further design and implementation details are presented in section 4.2.3.

- Domain model. The domain model is used to calculate if the learner is answering the questions in the learning task correctly. Based on details in the scenario script, the current scenario state, and the learners' interaction with the learning activity, a calculation can be performed regarding the learners domain knowledge. Further design and implementation details are presented in section 4.2.3.

- Learner model. The learner model is the tutoring systems representation or model of the learner. It records details about the learner. Further design and implementation details are presented in section 4.3.

- OLM interface. The learner can interact with the OLM interface on the touchscreen. Updates to the learner model are sent to the OLM interface by the scenario manager. Further design and implementation details are presented in section 4.4.3.

- Pedagogical model. The model determines the behaviours that the robot should perform based on the details in the scenario script, the current scenario state, the learner interaction with the learning activity, the results of the domain model, and the history in the learner model. Further design and implementation details are presented in section 4.5.

- Fully autonomous robotic tutor. The robot tutor executes the behaviours presented to it by the pedagogical model via the scenario manager. Further design and implementation details are presented in section 4.6.

The system is implemented using the Model-view-controller[1] architecture pattern. This decouples the internal representation of information from the way this information is displayed and controlled by the user. The model manages information or state, it responds to requests to view the information from the view, and it updates the information based on the request from the controller. The view presents the information to the user based on the information provided by the model. The controller responds to the user interaction and modifies the state of the model. This architecture is commonly used in graphical user interfaces and supports the reuse of components. This architecture works well for this application as it allows the learner task interface, the OLM interface, and the robotic tutor to make use of the same models. For example, the robot is able to act as a view for the OLM by speaking aspects of the model, in addition to the OLM interface, as was presented in section 3.6.

The architecture is event based. There are a number of events that can trigger the learning task or OLM interfaces to update or the robot to execute a behaviour. The events are: learner interactions with learning activity, such as an answer attempt, using a tool, or changing activity; learner interaction with the OLM, selecting a competency in the OLM to inspect the detailed view; timeout, when there has been no robot or learner activity in a timeout period; and session start and end events. When one of these events occurs, the system evaluates the event and decides if the

[1]https://en.wikipedia.org/wiki/Model%E2%80%93view%E2%80%93controller

task or OLM interfaces should update, or if the robot should execute a behaviour based on the pedagogical model or scenario script.

An example of the event based architecture is demonstrated in Figure 4.2. This shows the flow of a learner initiated event through the system modules resulting in updates to the learning task and OLM interface and the robot executing a behaviour:

1. The learner performs an action in the activity, such as an answer attempt.

2. The learning task interface sends the event to the scenario manager. The scenario manager determines that this is an answer attempt and the domain model is passed the event.

3. The domain model uses the scenario state and the answer attempt to determine the learner domain knowledge. The results of the answer attempt are passed back to the scenario manager. The scenario state and learner model are updated.

4. The pedagogical model uses the results of the answer attempt, the scenario state, and the learner model to determine the pedagogical actions of the robotic tutor. A behaviour for the robotic tutor will be proposed by the pedagogical model.

5. The scenario manager will then send updates to the learning task interface, the OLM interface, and the robotic tutor to execute. These updates are synchronised. So if the answer attempt was successful, the updates would be:

- 5a. The learning task would display the next step in activity.
- 5b. The relevant competencies in the OLM interface would update with an animation.
- 5c. The robotic tutor would make a positive beep and then read out the instructions for the next step in the activity.

More detailed explanations for the pedagogical support from the robotic behaviours are described in the relevant sections of the studies. The pedagogical model (based on the ideal model of SRL described in subsection 5.2.1) takes into account the actions in the task and the learner model and may cause the robot to act, this process is discussed in chapter 5 and subsection 5.2.2.

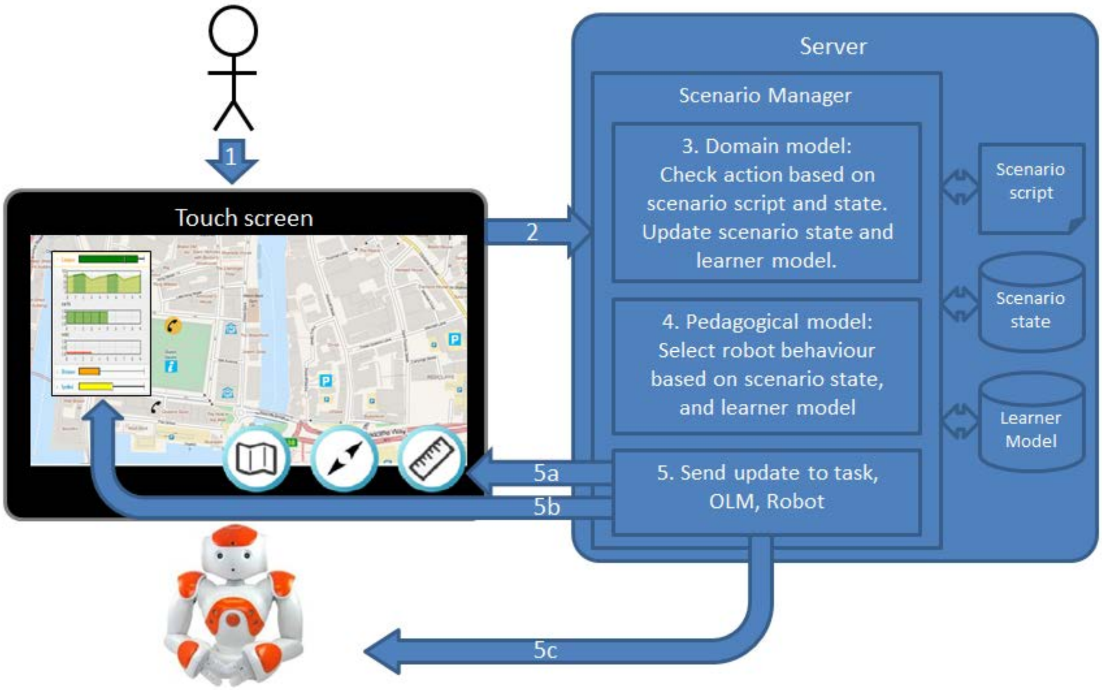

Figure 4.2: Event based architecture. Showing flow of a learner initiated event through the system modules resulting in updates to the learning task and OLM interface and the robot executing a behaviour.

The views of the learning task interface and OLM interface are implemented in JavaScript, HTML, and CSS which are particularly suited for making user interfaces. Further details on the technology and libraries is detailed in section 4.2.3 and section 4.4.3. The robotic tutor is controlled using a Java library available from the manufacturers of the robot. The controller and models running on the server are implemented in Java using the Spring Framework. The Spring Framework provides a high level of infrastructural support for plumbing the views, controllers, and models together[1]. This includes support for messaging and persistence.

[1] https://projects.spring.io/spring-framework/

4.2 Learning task

This section describes the specification, development, and implementation details for the learning task. The learning task allows the learner to practice their map skills in an open-ended setting which allows the practice and demonstration of SRL skills. There are a variety of activities and tools for the learner to choose from. The task ties in to the geography curriculum as it allows learners to practice basic map reading skills and can also be tied into other lessons that the teachers teach in the classroom.

The learning task has been iteratively improved upon from a paper mock-up in section 3.5. In section 3.6 a simple non open-ended activity was used. The task was made more open-ended for section 3.7, section 6.2, and section 6.3. In section 6.3 there was another activity added to the task; the wind farm activity.

4.2.1 Learning task specification

The learning task specification has been created based on requirements elicited from the teacher interviews, the curriculum for the learners, background literature review, and a review of existing learning activities.

From a usability perspective for the learner the interface needs to clearly display text, the learning task, the controls, and the objectives. The interface needs to make it easy for the learner to provide answers and to use the tools provided.

The teachers in section 3.4 requested that the learning scenario as a whole needed to be robust and not require any interaction from the teacher to ensure that it is working correctly. If there are technical issues with the activity it would risk the learners becoming disengaged from the learning activity.

The robot should be aware with how the learner is interacting with the learning task. It is useful for the robot to be able to read out objectives of a learning activity. The robot should also be able to demonstrate some aspects of the learning activity to the learner. However, as the focus of this research is regarding SRL the robot does not need to have a high degree of control of the learning activity as the learner should be placed in control.

Pedagogical specifications

The primary aim for this learning scenario is for the learner to be able to practice and develop SRL skills. The primary requirements to support this were elicited from UCD studies described in study 1 (section 3.4), study 2 (section 3.5) and the England and Wales national curriculum for geography (DfE, 2014) to specify the learning task. However, requirements on instructional design recommendations from cognitivist and constructivist theories (Ertmer and Newby, 1993), and conditions to allow the practice of SRL skills (Zimmerman, 2008) were also considered.

The domain should enable the learning task to support the pedagogical specifications below. The teachers in section 3.4 did suggest an example task where the learner is required to choose the location of a new football stadium in the local area.

The task specification is tailored to the developmental age of the learners by using *Developmentally Situated Design Cards* (DSD cards) (Bekker and Antle, 2011). These cards were created to make age specific information about children's developing cognitive, physical, social, and emotional abilities readily accessible for designers (Bekker and Antle, 2011). Each card gives age specific information about a child's developing ability and how the design of the learning activity or interaction can better address that ability. The DSD card set consists of 42 cards describing 14 developmental areas/abilities for 3 age groups (5 to 6, 7 to 9, and 10 to 12). The cards for the age range 10 to 12 were selected for the cognitive and emotional abilities that applied to the learning scenario discussed with the teachers. These were: problem solving,(Figure 4.3); attention,(Figure 8.9); instructions,(Figure 8.11); self-esteem,(Figure 8.13); perspective taking,(Figure 8.12); and understanding & empathy,(Figure 8.14). For example, the card for problem solving defines problem solving as “Children in this age group are independently practising understanding, evaluating, and solving problems.”, the design tips are “Does the design help a child develop independent learning skills? Can the design encourage a child to try many different approaches to solve a problem? Can the design help a child pick the best solution from potential solutions they’ve generated?”. The card is shown in Figure 4.3. The cards that were used in this research have been reproduced in the appendix section 8.6. These specific design tips were used to help define the wind farm activity described later in the study. The design tips on the cards were then used to feed into the specification detailed below with the aim of increasing the chances of the learners in this age range enjoying and learning from the learning activity. The DSD cards can be downloaded from the link in the footnote[1].

Figure 4.3: Developmentally Situated Design Card for problem solving for children of 10–12 years of age

The principle requirements and specification for the learning task are as follows:

[1]http://www.antle.iat.sfu.ca/DSD/

- **Active involvement of the learner** in the learning process is a key principle of cognitive and constructivist theory (Ertmer and Newby, 1993), SRL (Zimmerman, 2008), and a recommendation of the DSD cards. The teachers in section 3.4 requested an engaging activity where the learner should feel that they were in control.

- **Planning** and setting goals and prioritising between different tasks are important parts of SRL. Learners should understand how to successfully manage their attention to meet their own goals. The learning task should provide the opportunity for the learners to create and execute plans. The teachers in section 3.4 requested that the learning scenario should support self-directed learning.

- **Supporting the learner to make connections** with previously learnt material is important from a cognitivist standpoint (Ertmer and Newby, 1993). This is also a key recommendation from the DSD cards as it could support the building of self-esteem.

- **Motivation** is an important part of engaging SRL processes and education in general. The teachers in section 3.4 requested a motivating and engaging activity, where the learners feel like they are progressing. The teachers in section 3.5 were observed to spend much of the interaction engaging and motivating the learner in the activity, i.e. teachers would congratulate the learners as they were making progress. The teachers in section 3.4 suggested that motivation and engagement is partly achieved through having a task of an appropriate difficulty level for the learner. Sometimes teachers might adjust difficulty by giving more or less scaffolding to the learner, for example using keywords, prompts, and questions. Teachers may also help the student break the problem into smaller pieces so the activities should be made of steps that could be decomposed by the tutor. The teachers might also give different activities to learners, so the task should provide activities of different levels. The most difficult activities should be more open-ended to provide a suitable level of challenge for the most able children.

- **Problem solving** skills are important for constructivist theory, SRL, DSD cards, and the England and Wales national curriculum for geography (DfE, 2014). When solving problems the learner must be able to select and deploy appropriate problem solving strategies as a key part of their SRL skills. The teachers in section 3.4 requested that the learning scenario support discovery learning which is linked to problem solving as it is learning through discovery.

- **Reflection or self-monitoring** is an important aspect of being able to solve problems at a low level and also set goals at a high level. Reflection was highlighted by teachers in both studies described in section 3.4 and section 3.5.

4.2.2 Learning task design

The learning task is designed for learners to be able to practice and develop SRL skills. The learning task is designed to support constructivist and socio-constructivist styles of learning, where the learner is placed in control and learns from experience (Ertmer and Newby, 1993). This fits well with the view of SRL as a process where the learner should set goals, select and deploy strategies, and self-monitor their effectiveness (Zimmerman, 2008). To that end the learning task (and scenario as a whole) has been designed so that it is able to support learning based on the cognitive and constructive theories. It is hoped that this will allow the learner opportunities to engage and practice SRL skills.

The learning task will take place on a large touchscreen. Answers and tools will use touchscreen rather than typing. Answers will be multiple choice. This allows the system to be more constrained and there is no need to evaluate text with natural language processing or handle issues with typing.

The domain of geography has been selected as this enables the creation of a learning task that has the freedom for the learner to use and develop SRL skills. Creative domains such as languages or art and design present issues with automated evaluation of the learner's abilities. While maths and languages can be structured which makes the evaluation of learner abilities more straightforward, this structure limits the decision making and analytical skills that could be utilised. Domains such as geography, science, design and technology, and computing that build upon other skills and require experimentation, evidence evaluation, and problem solving should provide a suitable domain for the practice of SRL skills. It was found in the teacher interviews described in section 3.4 that teachers already used this domain to create learning activities that were open-ended and required the learners to use SRL skills. Such activities can allow a range of competencies (e.g. map-reading, map sketching, mapping, geographical argumentation, ethical judgement (see (Rempfler and Uphues, 2012))).

A review of the England and Wales national curriculum for geography (DfE, 2014) was conducted which asks for the pupils to be able to:

- use atlases, globes, maps at a range of scales, photographs, satellite images and other geographical data;
- ask geographical questions, thinking critically, constructively and creatively;
- analyse and evaluate evidence, presenting findings to draw and justify conclusions; and
- solve problems and make decisions to develop analytical skills and creative thinking about geographical issues.

As the aims of the curriculum are in line with the SRL skills, this was considered to be a good domain in which to offer SRL scaffolding. The study described in section 3.5 was used to test the map based activity and it found that the teachers were using it to scaffold SRL skills, particularly prompting the learner to reflect on their developing skills.

Design to support pedagogical specifications

- **Active involvement of the learner** is supported by making the learner responsible for the choices in the task. It is up to the learner to set goals, evaluate learning, identify gaps in learning, draw on appropriate resources, and select and carry out learning strategies. This was highlighted by teachers in the interviews discussed in section 3.4 and teachers were observed doing this in practice in study 2 (section 3.5). In practice, active involvement for this learning task means giving the learner multiple options in the task. At a high level the learner is given the choice of what difficulty of activity to attempt so that they are not simply presented with questions of increasing difficulty. The presence of the OLM is aimed to support the learner in reflecting and identifying gaps in learning.

- **Planning** skills are supported by allowing the learner to select different activities. The task allows easy switching between related tasks and it is clear which skills are present in each activity. This allows setting goals and prioritising between different tasks, which is an important part of SRL. The structure of the activities described below allows the learner to practise individual skills before practising them together. The task supports a learner in understanding how to successfully manage their attention to meet their own goals. Teachers gave examples of supporting planning in the interviews described in section 3.4. From background on OLM subsection 2.3.4, an OLM can further support SRL when the learner is able to control their own learning in the learning scenario, e.g. undergraduate students were able to use an OLM to identify misconceptions and better allocate their effort to meet their learning needs (Bull et al., 2010). Students can use an OLM to select the most appropriate problems that may allow more effective learning (Mitrovic, 2007).

- **Supporting the learner to make connections** is supported by providing the learner with multiple activities where knowledge and skills may be used in slightly different ways. The learner can start with more simple activities to practice basic skills and move up to more complex open-ended questions that may require complex strategies to solve. This can help the learner recognise how certain skills can transfer to a variety of different activities. Icons are shown on each activity to indicate how specific skills relate to the different activities. The selection of activities can also support the learner to transfer knowledge and skills as the skill may be used in slightly different ways in each activity.

- **Motivation** is supported in that task by providing a series of activities the learner can complete successfully, ranging in difficulties from easy to progressively more difficult. This allows the learner to select an appropriate difficulty level to keep themselves engaged and motivated. The activity also shows the learner when they are doing well in the form of basic 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. Additionally, the OLM as part of the activity can provide motivation or build self-esteem, by highlighting when a learner has improved a skill.

- **Problem solving** skills and development of these skills are supported by setting problems and allowing the learner to try different approaches to solve a problem. There is a selection of tools in each activity which could be used to solve the current objective. Within more difficult activities the learner will need to use more complex strategies to solve the problem.

- **Reflection or self-monitoring** is supported with some basic feedback in the task as described above. In addition to this, the OLM supports reflection and can help the learner evaluate different problem-solving approaches while in an individual activity. The OLM can also be used at a high level to decide which activity to do next. This is discussed further in the following OLM section (section 4.4).

In summary the learning task supports the learner in practising and developing SRL skills by setting problems and then placing the learner in control, allowing the learners to set goals and prioritise between different tasks, and solve problems using a variety of tools.

Activities

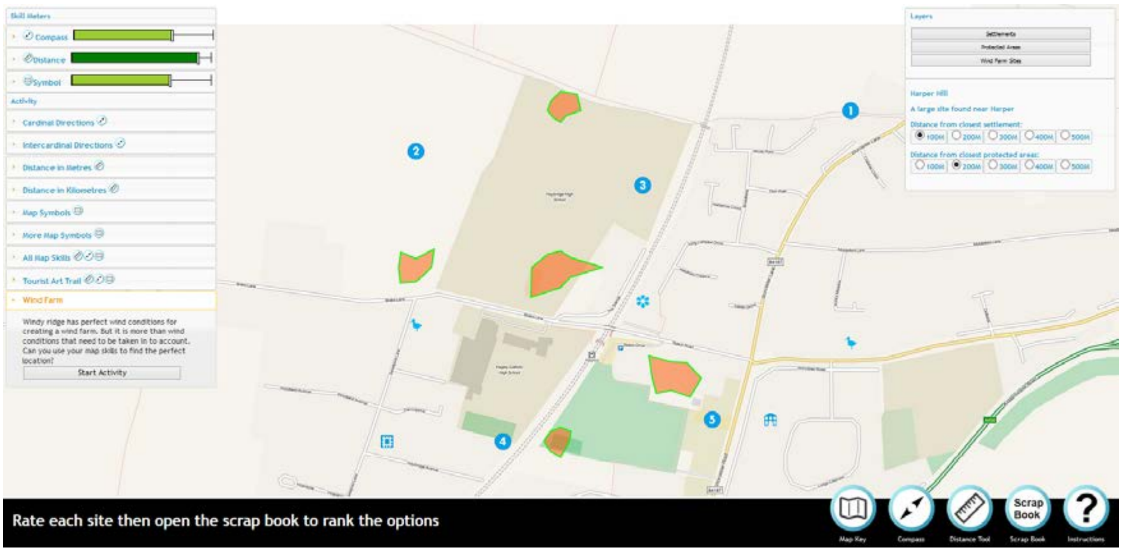

Figure 4.4: The wind farm activity

The learner has a choice of activities of varying difficulty that allow them to practice map reading skills for distance, direction, and map symbols. All of the activities allow the learner to interact with maps and geographical data. The activities require the learner to evaluate evidence, solve problems, and make decisions. The resources at Ordnance Survey MapZone[1], Digimap for Schools[2], and BBC Bitesize[3]

[1] http://mapzone.ordnancesurvey.co.uk/mapzone/giszone.html
[2] http://digimapforschools.edina.ac.uk/
[3] https://www.bbc.co.uk/education/subjects/zbkw2hv

were used as inspiration for the activities. Each activity can focus on a different competency, skill, knowledge or combine all. The more simple activities just focus on competency e.g. a compass direction activity where the learner can practice the cardinal direction of north, south, east, and west. The most advanced activity is to decide the best location for a wind farm based on distances and more difficult inter-cardinal directions. Activities are made up of a number of steps, and once all of the steps have been completed they will loop so that the learner can practice as much as they like. The activities available are:

- Cardinal Directions: Allows the learner to practice compass/direction competency. The step objectives are in the form of "Click the blue circle X of the star". Where direction can be north, east, south, or west.
- Inter-cardinal Directions: Allows the learner to practice inter-cardinal directions. The step objectives are in the form of "Click the blue circle X of the star". Where direction can be north, north-east, east, south-east, south, south-west, west, or north-west.
- Distance in Metres: The learner can use either the map scale or a distance tool to practice distance competency. The step objectives are in the form of "Click one of the blue circles X metres from the star".
- Distance in Kilometres: This activity is slightly more complex than the distance in metres as the learner must convert between metres and kilometres. The step objectives are in the form of "Click one of the blue circles X kilometres from the star".
- Map Symbols: The learners can practice recognition of the map symbols in a more interactive way than by simply looking at the map key. The symbols used are from the Ordnance Survey Legend 1:25000 scale[1]. The step objectives are in the form of "Click the X symbol".

[1]https://www.ordnancesurvey.co.uk/docs/legends/25k-raster-legend.pdf

- All map skills: This activity combines all of the map skills from previous activities. It is more difficult as there are multiple parts to each step. The step objectives are in the form of “Drag the X symbol to the point Y metres Z of the star”.

- Art trail: This combines all skills and increases in difficulty moving from cardinal to inter-cardinal directions. At the end of the activity the learner must place a statue on the map based on clues found on the trail. It uses the map skills in a slightly different way to the above activities. The back story for the task is that the learner is helping to plan an art trail for a city. The trail is made up of a number of steps that increase in difficulty through the activity. Each step will involve the learner choosing the next feature/symbol in the trail based on the direction, distance from the current point in the trail. The activity is shown in Figure 4.5.

- Wind farm: This activity is designed to be a more sophisticated test of a learner’s problem solving skills. This uses the distance and direction skills in a slightly different way from the previous activities. The use of problem solving skills is emphasised by the learner needing to rank locations based on notes that they have taken in the activity. The learner should rank the best three sites for a wind farm out of five taking into account a number of different perspectives. The learner was required to open the scrap book and rank the top three potential sites out of five and then submit the ranking for evaluation. The learner was then given feedback on each of the selected sites. The learner was able to take notes throughout the activity by selecting a site and using radio buttons to record details about the site compared to the others. The learners could also select five towns and five protected sites to find out more details. The activity is shown in Figure 4.4.

Difficulty levels

There are a number of activities developed at differing difficulty levels. The study described in section 3.5 was used to gauge the difficulty level of the activities, this was achieved by starting the activity with easy questions and then increasing the difficulty as the activity progressed. The activity can be viewed in section 8.3. This allows the difficulty of the learning task to be adjusted through the learner doing different activities or by being supported by a teacher or the robotic tutor.

4.2.3 Learning task implementation

The learning task is implemented following the high level specification and design in subsection 4.1.3. The learning task is made up of the learning task interface, domain model, scenario manager, scenario state, and scenario script. The learning task interface is implemented to run inside a web browser using JavaScript and it communicates to the other modules using JSON. The other components are implemented inside of a web-server in Java using the Spring Framework.

Learning task interface

The learner interacts with the learning task interface on the touchscreen. The content displayed in the learning task interface is determined by scenario script and updated by the scenario manager. The learning task interface shows the current activity to the learner.

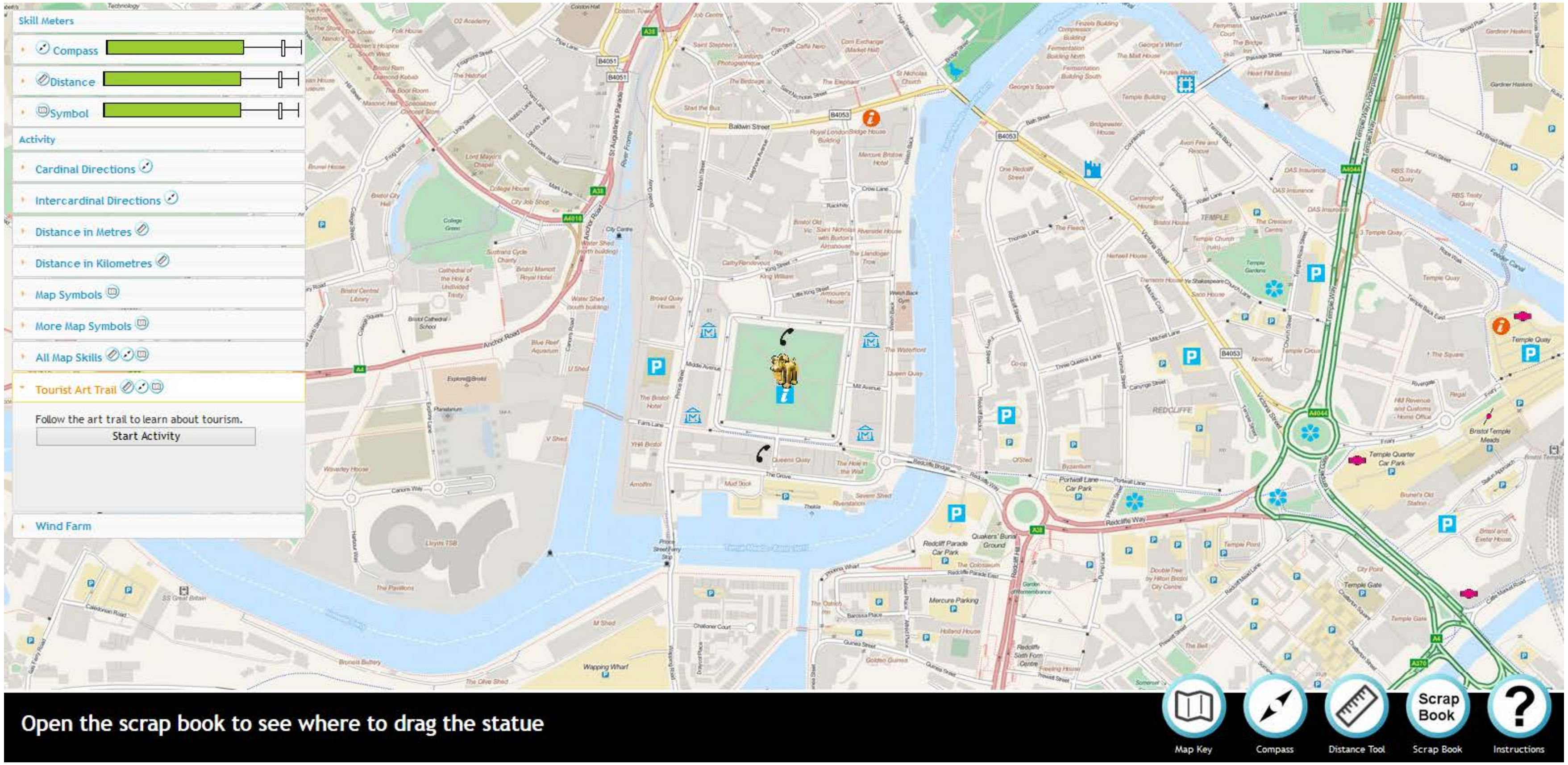

Figure 4.5: Learning task interface: map, showing the art trail activity (centre); current objective, prompting the learner to open the scrap book (bottom left); activity selection menu (left), allows learner the choice of activities; tools (bottom right), can be used by the learner to assist with the activity

Map The majority of the learning task interface is a large map which is where the learner provides answers for the steps of the currently selected activity. The implementation makes using the OpenLayers[1] JavaScript library which is able to display an interactive map from a number of sources. The relevant map tiles needed by the learning task were stored on the file system of the server so that access to the Internet was not required for map data. The map tiles were originally downloaded from Open Street Maps[2]. OpenLayers allows objects to be placed on to the map for the learner to interact which in many cases is how the learner to provide answers in the learning task.

One issue found in a pilot study was that learners may try and click the map in quick succession. So when the learner selects an item of the map in an answer attempt then the map is briefly greyed out so no further interactions are available until the server has had a chance to evaluate and respond to the learner. This is a very brief period, typically less than a second. This also potentially gives some time for the robot to talk.

Current objective The current object of the step of the selected activity is shown in the black bar at the bottom of Figure 4.5. This bar can flash green if the answer to the step was correct, and red if the answer to the step was incorrect. The text is white, large, and easily readable.

Activity selection menu The activity selection menu is visible towards the left of Figure 4.5. Each activity has a symbol representing the type of activity it is. The menu is an accordion menu. When the learner selects the activity the accordion opens to provide more information about the activity. At this point the learner can select the "Start Activity" button to change to that activity.

[1]https://openlayers.org/
[2]https://www.openstreetmap.org

Tools The learner is provided with a number of tools to assist them with the task. The learners have the option to open a map key, use a distance tool, display a compass onscreen, and to view previous clues in a scrap book; the buttons to enable these tools are in the bottom right of Figure 4.5. The tools are:

- Compass tool: The learner is able to enable and disable the compass tool. Enabling the compass tool will cause an image of a compass to appear over the centre of the map to assist with the learner with identifying the correct direction.

- Map Key tool: The learner is able to enable and disable the map key. Enabling the map key will show a pop-up window towards the right side of the learning task interface. This pop-up shows a key with the images of all of the map symbols along with their name. The symbols used are from the Ordnance Survey Legend 1:25000 scale[1].

- Distance tool: The learner is able to enable and disable the measuring tool. The tool allows the learner to measure the distance between two points on the map. The learner taps once on the learning task interface where they want to measure from, and then tap again where they want to measure to, the distance between those two points is displayed on the map.

- Art trail scrap book: As the learner carried out the art trail they received clues. These were placed in the scrap book. The learner needs to open the scrap book at the end of the activity to identify the location to place the statue.

- Wind farm notebook: The learner was able to take notes throughout the activity by selecting a site and using radio buttons to rate details about the site compared to the others.

[1] https://www.ordnancesurvey.co.uk/docs/legends/25k-raster-legend.pdf

- Wind farm scrap book: The learner was required to open the scrap book and rank the top three potential sites out of five and then submit the ranking for evaluation. The learner was then given feedback on the each of the selected sites.

Communications When there is any interaction by the learner in the learning task interface this creates an event that causes a JSON message to be sent to the scenario manager. If the learner has answered a step by selecting a point or object on the map, then the latitude and longitude of the point or the details of the object are sent to the scenario manager for the domain model to evaluate. If the tools or menus are used then details are sent to the scenario manager for the pedagogical model to evaluate. If the learner has selected to change activity then this information is included for the scenario manager to send details of the activity to load. When the learner gives an answer attempt the screen is greyed out briefly while this attempt is evaluated, the screen is not greyed out for other interactions.

When the learning task sends an event in the form of a JSON message to the scenario manager the learning task interface listens for a response in the form of a JSON object that contains the details of what to show inside of the learning task interface. If no events have been sent to the scenario manager the learning task interface continuously polls the scenario manager to check if any timeout events or start or end of session events within the scenario manager have caused there to be an update to the learning task interface. This JSON message from the scenario manager contains details of what should be shown in all aspects of the learning task interface. For example:

- The activities which should be available in the activity menu.
- The area of the map to display for the selected activity.
- The objects to display on the map for the selected activity.

- The current objective for the step of the selected activity.
- The opening or closing of a tool in line with a message to synchronise with a robotic tutor behaviour.

Scenario builder and activity building tool As part of the learning task interface there is a scenario and activity building tool. This can be used to create and fine tune activities using the interactive map. It is used to place reference points and objectives on the interactive map and then record these as steps for activities in the scenario script described in section 4.2.3. This was used to create the art trail and the wind farm activities. There is also a tool to generate the more simple distance, direction, and map symbol activities. To create the activity a central reference point in longitude and latitude is provided along with the type of objectives to be generated, the tool then generates questions in relation to that point, including the text to be displayed to the learner. This means activities can be quickly generated and set in the region of the learners' school.

Scenario manager

The scenario manager module or controller ties all of the other learning scenario modules together. The module listens for events from the learning task and OLM interfaces and coordinates communications between the other modules. When an event is processed by the scenario manager it may conclude with the learning task and OLM interfaces updating and the robotic tutor performing a behaviour. The scenario manager controller is implemented inside of a web server in Java using the Spring Framework. The scenario makes used of the scenario script and scenario state to determine what should be displayed on the learning task interface as described above.

Scenario script The scenario script contains information about the learning scenario as a whole. This includes the activities available to the learner in the learning task and the length of the learning session. When the robotic tutor is used in studies in section 3.6, section 6.2, and section 6.3 the scenario script also contains details on what the robotic tutor says in the introduction to the learning task. The scenario script is stored as an XML file. While the file is primarily generated in a programmatic manner with the tool described above, it can also be edited with a text editor for fine tuning. The scenario script can be queried/inspected to understand the competencies and knowledge that are covered in an activity, this information is used later by the pedagogical model in conjunction with the learner model to understand if a learner has mastered the content in an activity.

Scenario state The scenario state tracks the learner's progress through the scenario script. It records the activity and activity steps that the learner has undertaken. This is stored in memory but is also recorded to XML file in case there is an issue with the learning task and also for later analysis.

Logging In addition to recording the scenario state, the scenario manager also logs all interaction events of the learner with the learning task interface for later analysis. The includes detail regarding where the learner has used tool, the activities undertaken by the learners, and the session start and end times. This is recorded to an XML file for later analysis.

Domain model implementation

The domain model is used to calculate if the learner is answering the questions in the learning task correctly. When the learner makes an answer attempt, the scenario manager forwards this attempt to the domain model along with the details of the activity step. The domain model then has the information that it needs to be able to calculate if the learner is correct, partially correct, or incorrect. The domain model can evaluate answers given against the objective in terms of the direction, distance, symbol, ranking, or a combination of these constraints. It is possible to get an answer partially correct if for example the learner identifies the correct distance but an incorrect direction.

An activity step objective is in the form of *"Drag the nature reserve symbol to the point 100 metres north of the star"*. The domain model is then given the details of the symbol that learner has selected and the longitude and latitude of where they have dragged it to. The domain model has the longitude and latitude of the star reference point and the target distance, direction, and symbol from the scenario script. The evaluation is carried out as follows:

Distance evaluation. The domain model calculates the distance between the longitude and latitude coordinates of where the learner dragged the symbol and the reference point. It records: the distance, the target distance, and if the constraint is correct in the answer attempt detail.

Direction evaluation. The domain model calculates the direction between the longitude and latitude coordinates of the reference point and where the learner dragged the symbol. It records: the direction, the target direction, and if the constraint is correct in the answer attempt detail.

Symbol evaluation. The domain model simply records: the symbol selected by the learner, the target symbol from the scenario script, if they match, and if this competency is correct in the answer attempt detail.

Ranking evaluation. For the wind farm activity the learner is evaluated on how close their evaluation of the ranking is to the target rank. The domain model simply records: the ranking selected by the learner, the target ranking from the scenario script, and if competency is correct in the answer attempt detail.

The results of these evaluations are returned to the scenario manager to be passed on to the learner model and used as the basis for updating the learning activity interface, the learner model, the pedagogical model, and potential robotic tutor behaviours. For example, the learning task interface will flash green if all of the constraints/competencies have been answered correctly before showing the next activity step objective. This communication is achieved with the AnswerAttempt object with a collection of AnswerAttemptItems.

Versions

The learning task has been iteratively improved upon from a paper mock-up in section 3.5. In section 3.6 a simple non open-ended activity was used. The task was made more open-ended for section 3.7, section 6.2, and section 6.3. In section 6.3 there was another activity added to the task. Details of the versions are shown in Table 4.1

Table 4.1: Learning Task Versions

Study	Version Notes
section 3.5	Paper based task. section 8.3
section 3.6	Testing all symbols, no activity choice.
section 3.7	All activities other than the wind farm activity
section 6.2	All activities other than the wind farm activity. Fully autonomous robotic tutor
section 6.3	All activities. Fully autonomous robotic tutor.

4.2.4 Learning task summary

In summary, the learning task supports the learner to practice and develop SRL skills. This is done with the active involvement of the learner, allowing the learner to plan, supporting them to make connections, structuring the task in a motivating way, providing problems that require problem solving skills, and also supporting reflection and self-monitoring.

4.3 Learner model

The learner model is the tutoring systems representation or model of the learner. The learner model allows the pedagogical model to adapt and personalise SRL support to the learner. The learner model is also the basis for the OLM skill meters, the robotic tutor's adaptive and personalised domain support, and SRL scaffolding behaviour.

The learning model has been iteratively improved upon from the initial learner model developed for section 3.6. The learner model was updated to support the OLM specification for section 3.7. Then the learner model was updated to support personalised SRL scaffolding for section 6.2. Finally, for section 6.3 the learner model was updated to support personalised domain scaffolding and for further SRL support in the form of session wrap-up and summaries.

4.3.1 Learner model specification

At a high level the specifications are that the learner model should contain the information required for the OLM and the information required by the pedagogical model to personalise and adapt domain and SRL support.

The learner model should contain the information required for the OLM to externalise the learner model in a way that is interpretable by the learner (Bull and Kay, 2010). This information should be sufficient to promote reflection and support the learners awareness of their developing skills and knowledge, which can help planning and decision-making (Bull and Kay, 2013). The teachers in section 3.4 discussed a competency based approach to measuring learner skills, so the learner model should record the changes in learner skill or competency levels. Most OLM that are inspectable by the learner focus on knowledge-related attributes. So in addition to the high level competency approach the learner model should also include evidence of a learner's knowledge.

The learner model should contain the information needed for the pedagogical model to personalise and adapt the autonomous robotic tutor's behaviours to learner competencies and SRL skills. Specifications from the background research in section 2.2 suggest the robot should adapt to the learner's task performance, their level of engagement, affect, learning style, cognitive development, and SRL needs. Unfortunately the reliable detection of engagement, affect, and learning style is not available so the learner model is only able to capture the learner's task performance via an interaction with the learning task interface.

Specifications from the background research in section 2.2 specifically indicate that the support should adapt to learner difficulties. It was observed in section 3.4, section 3.5, and section 3.7 that teachers did not want students to become stuck or demotivated. This means that the learner model should accurately reflect areas where the student has difficulty so that the pedagogical model can accurately suggest support for that area. In the detection of difficulty the learner model should go beyond simply recording correct and incorrect answers and attempt to take into account other factors such as the amount of time required for the learner to answer a question. As taking a longer amount of time to answer a question may indicate less proficiency.

As the focus of this research is in support and providing adaptive support for SRL skills the learner model needs to infer SRL skills from task performance or other actions in the learning activity. For example, the teachers in section 3.7 were observed to prompt the learners to achieve mastery of the activity that they were working on and demonstrate other good SRL behaviours. So the learner model should be able to indicate if the learner has mastered an activity or not.

To support reflection the teachers in section 3.4, section 3.5, and section 3.7 also suggested or demonstrated giving summaries of the learning progress. It has also been suggested that the use of memory to recall past activities can build a bond between the learner and the robotic tutor and can be beneficial to the learning scenario (Leite, 2013). So the learner model should support the ability to create summaries of a learning session.

The learner model should be as accurate a possible. If the information is inaccurate it could lead to the pedagogical model suggesting inappropriate support which could damage the interaction with the robotic tutor and damage the learning experience. In addition if the content displayed in the OLM is inaccurate the learners would stop trusting and using the OLM. The updates to the learner model should also be quick so that the learner model can be used by the pedagogical model to provide formative assessment and support.

4.3.2 Learner model design

The learner model records the learner's task performance, interaction with the learning activity, and the evidence as a result of the domain model evaluation to infer the learner's knowledge and calculate the competency or skill levels of the learner.

Competency /skill levels

The competencies or skills calculated by the learner model are intended to be used by the OLM to show a learner how their skills and competencies are developing. Competency based learner model is used as this is the approach that teachers requested in section 3.4 or used in section 3.5. There is an increasing focus on professional competency frameworks and the extension of the competency perspective to educational contexts, e.g. for language (Verhelst et al., 2009), for STEM literacy (Byhee, 2010), and for geography (Rempfler and Uphues, 2012). The details of how competency levels have changed over time is also available to the OLM and pedagogical model.

The skill levels are constructed using constraint based modelling (CBM). This is an approach whereby competency values are calculated by checking the learner's actions against a set of relevant constraints (Mitrovic, 2010). The learner model receives evidence about how a constraint has been met or broken from the domain model. This constraint is linked to a competency and the evidence of how the constraint is met or broken then contributes to the calculation of the skill level. The more recent evidence is given a higher weighting and the time taken to give an answer is also used to weight the evidence. Distance and direction are evaluated based on the learner identifying a point on a map that is at 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.

Learning progress and difficulty

The learning progress of the learner is based on indicators of the learner's skills, abilities and difficulties, measured through the learner's actions in the learning task. The task specific skills are recorded as competencies. The use of tools, touches on the screen, the attempts and time taken to answer each question, and the goals and progress through the activity is also recorded. This information feeds in to the competency values that relate to each task. Difficulties are identified when the learner has a low competency score or is taking an action that is not appropriate for the step in the activity.

Support for SRL scaffolding

The learner model contains details of the evidence for each competency which the pedagogical model queries to personalise and adapt to the learners SRL skills.

Learner details

The learner model also contains details of the learner; this includes the learner's name, age, and sex. The learner model is also able to record questionnaire and test data from pre and post-tests. This data can be processed and used in the next session in which the learner interacts with the robot.

4.3.3 Learner model implementation

The learner model is implemented as a Java module that runs in the same web server as the scenario manager, domain model and pedagogical model. The learner model interacts with these modules via direct method invocations. The learner model is persisted to a relational database (MySQL) for ease and efficiency of performing queries and also a XML file for ease of back up and analysis.

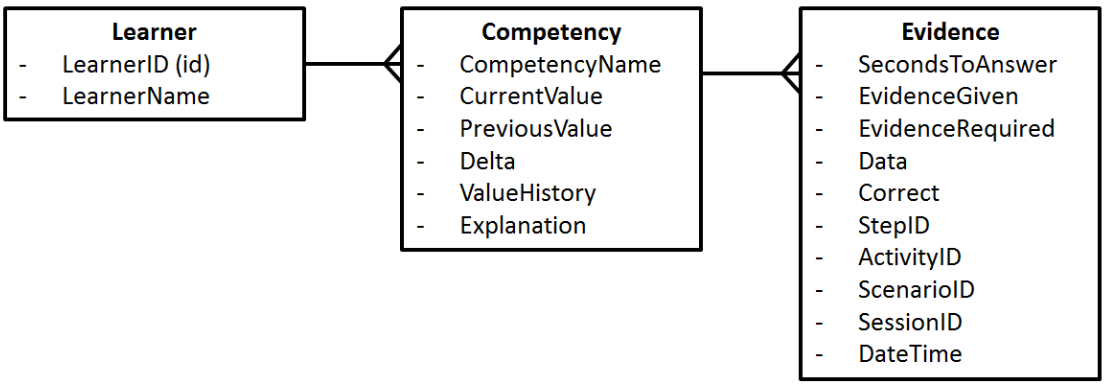

Figure 4.6: Learner model: entity relationship diagram

The entity relationship diagram for the learner model is shown in Figure 4.6. The learner model has a collection of competencies. A competency stores the high level value of the competency between 0 and 1, the previous value, the change, and an explanation of how the competency is changing. The competency has a collection of all of the evidence items that have led to the calculation of the competency value, the calculation is detailed below in the 'update of learner model' section. The evidence item contains the details from the domain model such as evidence given, evidence required, and if the evidence is correct. It also has the date, time, and seconds taken to answer the question. In addition there is a reference to the step, activity, scenario, and session.

Update of learner model

The learner model is updated based on the results from the domain model in the form of an answer attempt as described above. The learner model receives an AnswerAttempt object with a collection of AnswerAttemptItems. Each answer attempt item will match one of the competencies in the learner model (distance, direction, symbol, or ranking) and be used as evidence to calculate the overall level for that competency.

Each evidence item is given a score from 0 to 1. This is used later to calculate the overall competency value. For distance, direction, and symbol competencies the score is:

- 1, if the answer is correct and answered in under 20 seconds.
- 0.8, if the answer is correct and answered between 20 and 30 seconds.
- 0.7, if the answer is correct and answered between 30 and 40 seconds.
- 0.5, if the answer is correct and answered over 40 seconds.
- 0, if the answer was incorrect.

For the ranking competency the score is calculated as based on the distance between the ranking provided by the learner and the correct ranking. It follows that if the item should have been ranked first and the learner ranks it third then there would be a difference of 2:

- 1, if the difference is 0.
- 0.8, if the difference is 1.

$$new_competency_value = (evidence_item_score * decay_rate) + (previous_competency_value * (1 - decay_rate))$$

Figure 4.7: Weighted moving average calculation

- 0.6, if the difference is 2.
- 0.3, if the difference is 3.
- 0, if the difference is greater than 3.

To calculate the overall competency value a weighted moving average is used over the history of scores. A weighted moving average is used as it is sensitive to initial scores from the evidence but not affected by outliers as more evidence is provided. This means that the learner model value quickly settles on a value when starting out. If the learner makes a mistake later in the activity then the learner model will not suddenly drop. A decay rate is used so that more recent items of evidence are given more weight compared to preceding items. This means that the learner model values appear to be fairly accurate and consistent with evidence provided by the learner. The algorithm to calculate the competency value is similar to that in other learner modelling research (Johnson et al., 2013). All pieces of evidence for a competency are retrieved, starting with the oldest, then the calculation in Figure 4.7 is applied.

Learner model information used by the OLM

The learner model makes the history of the value of each competency available to the OLM. This means that the OLM can show the learner how their competencies are changing over time. The learner model also makes available a history of evidence grouped by the expected value. This allows the OLM to present to the learner a summary of the evidence provided to the learner model. For example this means that the OLM could show the learner a history of the evidence where the expected value was north, the learner can then see if they had been answering questions for north correctly. The OLM is described in detail in section 4.4.

Learner model information used by the pedagogical model

The pedagogical model is able to query the learner model to understand if the learner is having difficulties. For example if the learner is having difficulties in general then the competency will be low. If there are specific issues the pedagogical model can query for repeated issues with a particular type of evidence. As the learner model also records tool use and changes in activity, the pedagogical model can also look for indicators of good or poor SRL behaviours. For example, by querying if the learner is using a tool when there is evidence that they have issues with a competency, or by querying if the learner changes activity once they have shown evidence of mastering an activity. The information here can be used to provide prompts in the learning session or used to create a summary to aid reflection. This is described in more detail in section 4.5, section 4.6, section 6.2 and section 6.3.

4.4 OLM

OLM externalise the model that the system has of the learner in a way that is interpretable by the learner (Bull and Kay, 2010). Based on the study described in section 3.6 the OLM is used to show the learner high level skill levels in the form of skill meters, with the robotic tutor being used to highlight detail as required. The OLM developed here allows the learner to see a visualisation of the learner model so that they able to view an overview of their developing competencies and also drill down and inspect evidence of knowledge so that they can identify areas where they have strong or weak knowledge. Further details of the benefits of an OLM are described in subsection 2.3.4. An initial version of the OLM was developed for section 3.6, which shows skill levels and an explanation and is shown in Figure 4.8.

Based on the findings in section 3.6 the final version of the OLM was developed, this allows the learner to inspect the reason behind the skills levels, and is shown in Figure 4.9, this was used in section 3.7, section 6.2, and section 6.3.

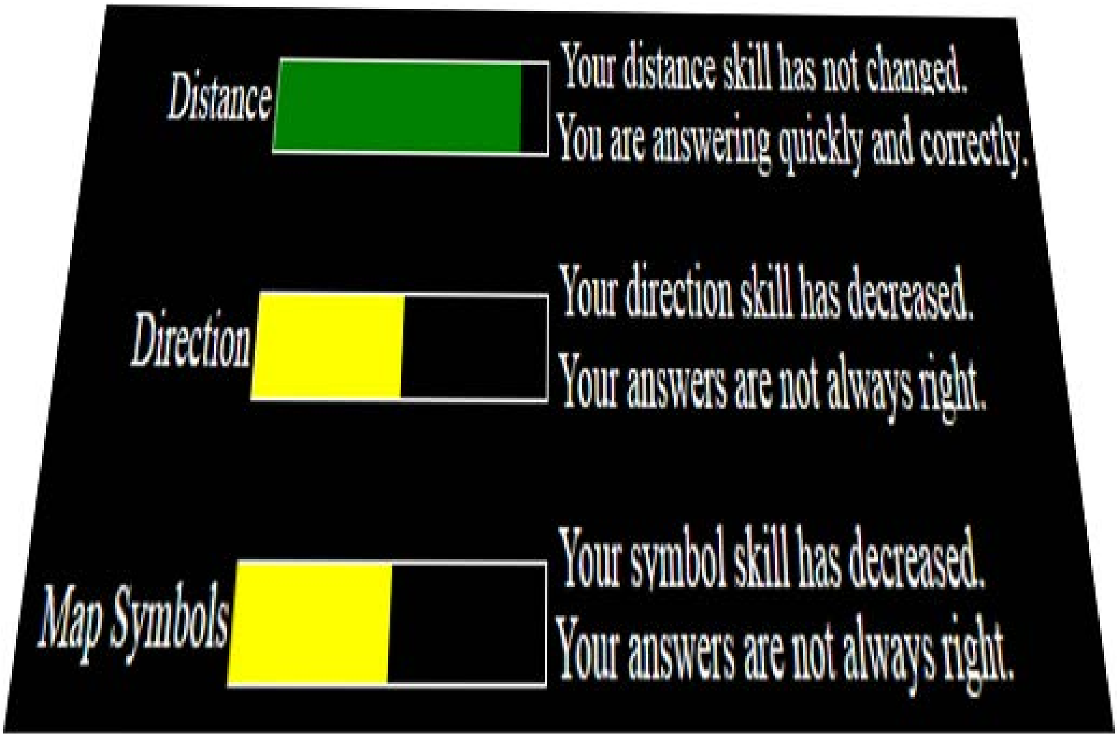

Figure 4.8: Initial OLM used in Study 3

4.4.1 OLM specification

The teachers in section 3.4 discussed a competency based approach which included progress bars to visualise skill level. The progress bars indicates that these participants wish to have a view of learning visible on the table top in line with OLM. In addition, the OLM should facilitate the kind of meta-cognitive behaviours considered important by all teachers. The request for being able to monitor learners is also in line with OLM being a tool to support teachers (Reimann et al., 2012). There is an increasing focus on professional competency frameworks and the extension of the competency perspective to educational contexts, e.g. for language (Verhelst et al., 2009), for STEM literacy (Byhee, 2010), and for geography (Rempfler and Uphues, 2012). This goes beyond many learning analytics visualisations (e.g. dashboards (Verbert et al., 2013)) to focus on supporting understanding of competencies. It follows that the OLM should be able to show changes in learner skill or competency levels.

As discussed in the background research in subsection 2.3.4 an OLM can support SRL by promoting reflection to raise awareness of understanding or developing skills, which can help planning and decision-making (Bull and Kay, 2013). OLM should allow the learner to see details of the evidence that they have provided to the learner model. This allows the learner to identify gaps in their knowledge.

The study performed in section 3.6 explored how a robotic embodiment might best support delivery of skill or competency based feedback with support of an OLM. The results show promise for the introduction of a physical embodiment when providing feedback concerning skill levels, however to gain the most advantage the robot should be used to explain and elaborate rather than simply state skill levels. It was found that robot should not state the information that can be seen easily at a glance at the OLM but should use the OLM to highlight and further explain the learner's developing skills. Therefore, the OLM interface should always be present on the screen and should show high level details with minimal text.

4.4.2 OLM design

The OLM that has been designed is similar to the one used in Mitrovic's KERMIT system (Mitrovic, 2007) described in section 2.3.4. This OLM design is chosen because KERMIT was also designed to use in an open-ended learning task (Mitrovic, 2005) and because the skill meters are accessible to learners. The OLM continuously displays a high-level summary of the learner's competencies, with more detailed information available by expanding the skill meter.

A competency based approach is used to present high level learner model values in a set of skill meters for each competency. The skill meters are visible at all times

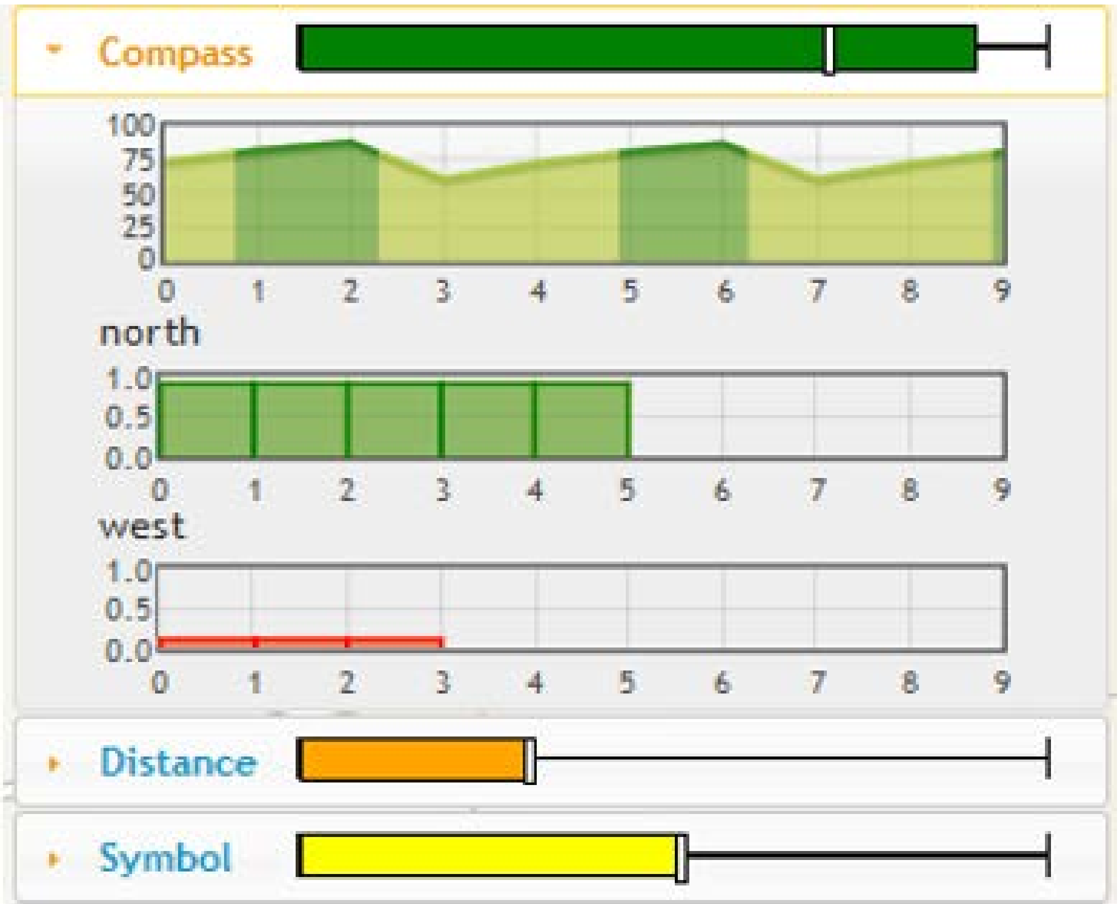

Figure 4.9: Final inspectable OLM used in Studies 4, 5, and 6

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 (Long and Aleven, 2013b). A view of the OLM is shown in Figure 4.10 where the high level skill meters are shown for Compass, Distance, and Symbol competencies; the Compass competency is expanded and this shows the history of the competency. For the OLM in section 3.6 an explanation for why the skill level is as it is also generated.

To support the learner in understanding gaps in their knowledge the OLM allows the learner to inspect a history of the most recent 10 pieces of evidence for each individual competency by clicking on the corresponding skill meter. 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. An expanded view of the Compass competency in the OLM is shown in Figure 4.10. This shows that the learner has answered north correctly 5 times, and west incorrectly 3 times. This enables the learner 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 assisting them to identify knowledge gaps, they can then fill these knowledge/skill gaps by selecting an appropriate activity or tool.

The pedagogical model has access to the underlying learner model and is able to use the social robotic tutor to interact with, highlight details in, and elaborate on the OLM interface that is presented to the learner. This approach enables the robot to use the OLM to prompt reflection and support co-regulation between the system and a user (Roll et al., 2014b). In future work it would be interesting to explore further interaction or negotiation between the learner and the OLM mediated via the social robotic tutor and touchscreen.

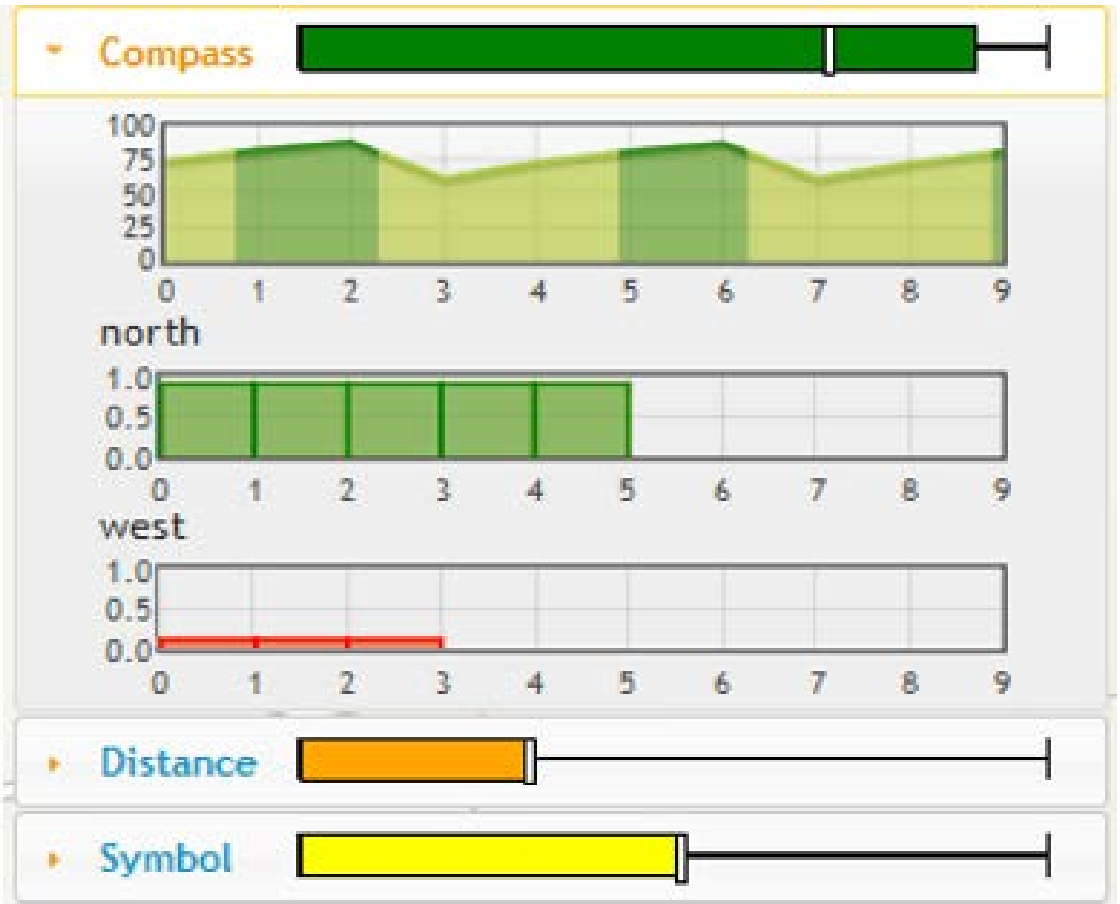

Figure 4.10: Expanded OLM: overall compass competency (high), level of the compass competency over the session (0–100%), 5 correct answer attempts for 'north' (A value of 1 with green), 3 incorrect answer attempts for 'west' (A value of 0 and red), overall distance competency (low), overall symbol competency (medium)

4.4.3 OLM implementation

The OLM is implemented as an interface to be displayed inside the same web browser as the learning task interface. It is written using JavaScript and it communicates to the other modules using JSON. Updates to the learner model are sent to the OLM interface by the scenario manager.

Initial OLM implementation

The initial version of the OLM implemented for section 3.6 is shown to the learner as a pop-up over the learning task after each answer attempt is made. There were three conditions, all three of the conditions provide the same information and explanation, however each condition varies the way the information was presented. The different conditions are show in Figure 4.11.

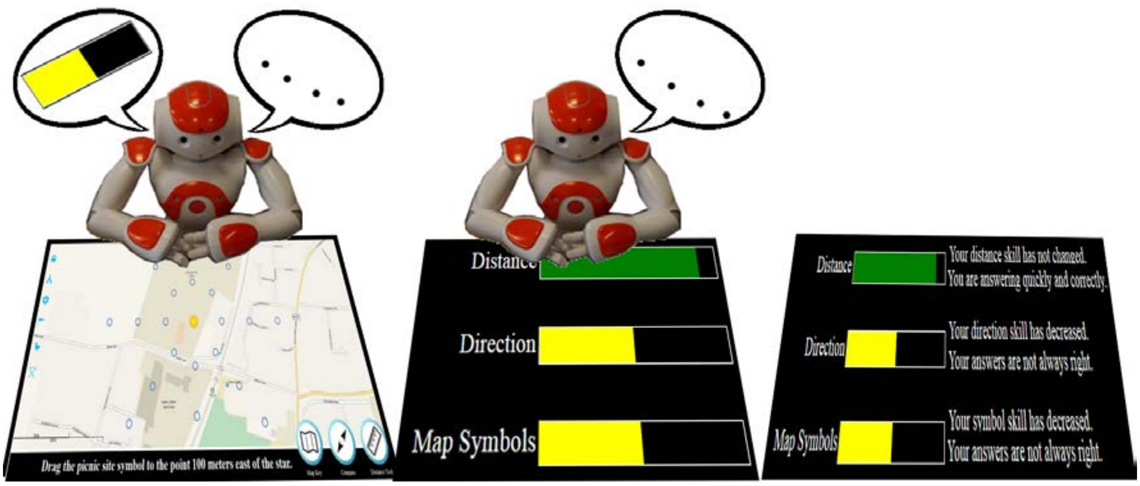

Figure 4.11: Conditions: (1) Full embodiment, (2) Mixed embodiment, (3) No embodiment

The learner was informed of their skill level followed by how that level had changed since the last step, increased, decreased, or stayed the same. This was then followed by an explanation. The value for the skill meters are calculated as described in the previous section. This calculation gives a value between 0 and 1 which is then used to give a skill level between the 5 values of very low, low, okay, good, and very good.

There are three possible explanations for the value of the skills meters. For each competency the explanation is created by looking at change in the competency value from the previous value and the current level of the value. If all competencies have updated in the same manner the explanation is summarised rather than explained multiple times. This saves time and avoids repetition. The explanations are as follows:

- If the competency has increased due to a quick answer or stayed the same due to the maximum skill level being reached the explanation is “You are answering quickly and correctly”.
- If the competency increases or stayed the same based on an answer that is correct but not given quickly the explanation is “You are answering correctly but sometimes a bit slowly”.
- If the competency decreases due to an incorrect answer or has stayed the same due to the lowest skill level the explanation is “Your answers are not always right”.

Final OLM interface implementation

For the implementation of the learner model in section 3.7, section 6.2, and section 6.3 the OLM is shown in the top left hand corner of the learning task interface. In the conditions where the OLM is present it is always available for the learner to interact with. The learner model is implemented as an accordion similar to the activity menu.

The high level value of each competency is always shown. The previous value of a skill meter is shown by a white bar. Updates to the skills meter are shown by the skill meter changing as an animation taking 3 seconds to change from the previous to the current value. The animations are implemented using the jQuery JavaScript library[1].

When a skill meter is expanded it shows a history of the values for that competency and a summary of the evidence grouped by the expected value from the domain model. This is shown in Figure 4.10. The history of the competency value and history of evidence are shown using charts implemented with the Flot JavaScript plotting library for jQuery[2]. The competency history shows the current competency value and the nine preceding values. Each evidence history line shows up to the 10 most recent attempts for that piece of evidence.

Communication with pedagogical model When the learner selects a competency to view the details, a message is sent to the scenario manager so that the learner model and pedagogical are informed of the event.

The pedagogical model can also cause the robot to perform some behaviours where the robotic tutor highlights some details in the OLM while causing a specific section of the OLM to expand. This is updated in a similar way to the learning task interface.

4.5 Pedagogical model

The pedagogical model determines the support offered to the learner based on the details in the scenario script, the current scenario state, the learners interaction with the learning activity, the results of the domain model, and the history in the learner model. The specific design of the computational approach to adaptively scaffold SRL is described in detail in chapter 5. This section gives the details for how generic pedagogical model can interact with the rest of the tutoring system.

[1]http://api.jquery.com/animate/
[2]http://www.flotcharts.org/

4.5.1 Pedagogical model specification

The pedagogical model must be able to adapt the learning task interface, the OLM interface, and the robotic tutors behaviours to the learner. As described in subsection 2.2.3 the adaptation can be based upon task performance, engagement, affective states, learning styles and the development needs of the learner. As the focus of this research is to increase SRL skills the main specification is for the pedagogical model to adapt based on task performance and indicators of SRL stored in the learner model.

This SRL support offered by the pedagogical model is based on approaches discussed in subsection 2.3.2 and subsection 2.3.3 and the UCD studies in chapter 3, particularly the study described in section 3.7. To summarise the pedagogical model should be able to demonstrate good SRL behaviour, provide prompts for SRL, and provide adaptive feedback. The detailed specification for domain and SRL scaffolding is given in chapter 5.

In addition to the SRL support the pedagogical model needs to offer some domain support and motivational support to the learner. This formative feedback should be provided in a timely manner as it is most effective when provided at a time when a learner can make use of it (Shute, 2008). However, the pedagogical model should also be able to make use of past events and activities as this can be used to build and maintain a good interaction (Leite, 2013).

The pedagogical and motivational support are based on the requests from teachers in section 3.4 and observations made in section 3.5 and section 3.7. The pedagogical model should keep the learner engaged and motivated. Teachers explained and demonstrated this by identifying the learners difficulties and adapting the difficulty of the task to the learner. To do this the teacher will highlight keywords (Anghileri, 2006) and make summaries of the question (Graesser et al., 1999). This can take the form of asking a lot of questions in order to redirect a student's efforts (Person and Graesser, 2003) e.g. "okay, so where is the scrap book?". The teachers provide considerable motivational support through positive feedback both verbally and with nods of encouragement. The teachers give very little negative feedback; this is similar to findings by Person (Person and Graesser, 2003), rather the teacher will give more sympathetic feedback and say things like “that is almost right”.

4.5.2 Pedagogical model design

Within the field of ITS, model tracing is a common approach to monitoring the way a learner works through a problem and determining when to provide support (Koedinger et al., 1997; Aleven et al., 2006). This is considered a cognitive model and is written as a set of rules than can capture both correct and incorrect behaviours (Aleven et al., 2006). With this approach the pedagogical model and the tutor does not offer support if the student is following the model (Koedinger et al., 1997; Aleven et al., 2006). However, if the learner deviates from the rules in the model the pedagogical model and tutor know the current state of the learner and can provide support that is adapted to the learners state and approach (Koedinger et al., 1997; Aleven et al., 2006). This is in effect an a ideal model and it is used to encourage learners that do not display ideal behaviours to move towards this model.

An alternative is constraint-based tutoring (Mitrovic et al., 2007), this builds upon the constraint-based model that is used to build the learner model. In this approach feedback is attached to the constraint, so that if the learner breaks a constraint then this feedback can be delivered to the learner, this will let the learner know that they have answered incorrectly, gives the reason why the answer is incorrect, and can direct the learner towards support related to that constraint (Mitrovic et al., 2007). This approach can also be used to deliver positive feedback when constraints have been met, although there needs to be further reasoning on top of the constraints to deliver this feedback in an appropriate manner (Mitrovic et al., 2013). This approach is more suited to highlighting issues in knowledge rather than creating feedback on a learning approach or meta-cognitive skills.

The approaches discussed can offer adaptive support, however they are most likely based on hand coded rules. Example-tracing tutors are similar to cognitive model tracing tutors, but use a behaviour graph created in an authoring tool instead of hand coded rules (Olsen et al., 2013). It is also possible to use machine learning techniques such as reinforcement learning to learn when it is appropriate to offer particular feedback (Chi et al., 2010).

A model tracing approach is used for the SRL tutoring as it is able to take into account other aspects than the constraints broken. It is also possible to build and evaluate a set of rules that make up the ideal model based on the observations made of the human teachers using this approach (Aleven et al., 2006). Another benefit is that when the learner is engaging in SRL skills the pedagogical model will not require the robot to act, which will give the effect of scaffolding SRL skills. The computational approach for adaptive SRL model is discussed in detail in section 5.2.

A constraint-based tutoring approach is used for the domain support. This is described in detail in section 5.2.2. If the distance constraint is broken a number of times the pedagogical model is able to request that the robotic tutor gives feedback to support that constraint. For example, if the learner has a difficulty with a direction, the robot could highlight a specific piece of knowledge by gesturing to the OLM, e.g *"Let us keep going, we need to focus on south-west"*, or suggesting that the learner uses the compass tool.

The pedagogical model determines the support offered to the learner via behaviours of the robotic tutor. The system has been developed as an event based system. There are a number of events that can trigger the pedagogical model, these are:

- Session start;
- Answer attempt, when the learner answers a step in the activity;
- Timeout, when there has been no robot or learner activity in the preceding 15

seconds;

- Interaction with the OLM;
- Interaction with the learning task activity menu;
- Interaction with the learning task tools;
- Tool selection, when the learner selects a tool to use; and
- Session end.

When one of these events occurs the pedagogical model is able to make decisions based on the details in the scenario script, the current scenario state, and the learner interaction with the learning activity, the results of the domain model, and the history in the learner model. The events detailed above and the detail recorded in the learner model should be sufficient to infer SRL abilities of the learner and if they require any domain or motivational support. The events detailed above allow the pedagogical model to take into account the learner's help seeking behaviours (Roll et al., 2011) and other SRL behaviours (Sabourin et al., 2012a). The events and information provided by the learning activity, domain model, and learner model should also be sufficient to highlight if the learner has issues with the domain knowledge. Unfortunately the system does not posse the sensing abilities to adapt to the learner motivation or affect. However, it should be possible to infer from the learning task interaction and learning progress if the learner is becoming demotivated. When the pedagogical model receives these events it can:

- Inspect task and activity progress. The scenario state contains granular activity based progress, e.g. current task details, difficulty, progress, number of correct and incorrect actions.
- Query the learner model to understand if the learner is having difficulties. For example if the learner is having difficulties in general then the competency will

be low. If there are specific issues the pedagogical model can look for repeated issues with a particular type of evidence.

- Review SRL indicators based on the learner model and task interaction. For example, by querying the learner model to see if the learner is using a tool when there is evidence that they have issues with a competency. The information here can be used to provide prompts in the learning session. Further details are described in section 5.2.

- Query the learner model for details over a session regarding the learners tool use, their competency levels, and details of activities completed. This enables the pedagogical model to create summaries and wrap-ups and show a memory of learner actions which can aid reflection and improve the interaction. Further details are described in section 5.2.

Based on the events detailed above the pedagogical model may cause the robotic tutor to offer some SRL, domain, or motivational support. It does this by asking the robotic tutor to execute a behaviour from a particular behaviour category.

4.5.3 Implementation

The pedagogical model is implemented as a Java module that runs in the same web server as the scenario manager, domain model, and learner model. The learner model interacts with these modules via direct method invocations. The pedagogical model is implemented as a set of hard coded rules in the code. The rules are shown in chapter 5 and the behaviours that the robotic tutor are shown in subsection 5.2.2. There are two versions of these rules, the first is for the short term study described in section 6.2, the second for the longer-term study described in section 6.3 which includes domain support, wrap-up, and summaries. The pedagogical model for the longer-term study builds upon the short term study.

Updates from scenario manager, learner model, task interface

As described earlier in this section and in subsection 4.1.3, when the learner performs an event in the learning task (an answer attempt or selecting the OLM, activity menu, or tool) that message is handled by the scenario manager and passed to other modules. The scenario manager requests behaviours after the domain model has checked the answer attempt and the learner model and scenario state have been updated. This means that the pedagogical model has the most up to date information in the learner model.

Pedagogical model updates sent to robot and OLM

The pedagogical model requests that certain behaviour categories and speech be carried out by the robot. As some of the robot behaviours have the robot opening the OLM to highlight details to the learner, OLM and robot behaviours are synchronised so that behaviours are executed at the same time that messages are sent to the learning task and OLM interfaces.

4.6 Fully autonomous robot tutor

The fully autonomous robot tutor executes the behaviours requested by the pedagogical model via the scenario manager. The robot acts in the role of a robotic tutor and social agent and provides SRL support, motivational support, domain tutoring, introduces the learning task and tools, and performs idle motions throughout interactions with the learner.

4.6.1 Robotic tutor specification

As discussed in the background chapter, particularly section 2.2, the robotic tutor should show awareness of the learner and provide appropriate support. Due to sensor limitations the robotic tutor will interact with the learner via the touch-table. Thus, the robotic tutor should be aware of the learner's interactions with the touchscreen and should also be able to interact with the touchscreen itself. For example, by demonstrating tools or the OLM.

The robotic tutor should be able to provide the support requested by teachers in section 3.4 and demonstrated in section 3.6 and section 3.7. This includes being able to deliver SRL support by highlighting details in the OLM, providing domain support in the learning task, and also motivational or social support. The robot behaviours should be designed to not detract from the learning of the learner. One major benefit of a robotic embodiment is the ability to offer subtle non-verbal feedback. The robotic tutor should not talk too much and take attention away from the activity, this also includes being careful to stop a learner trying to game the system to force the robot to talk. The design of the learning scenario and the robot's behaviour should give autonomy to the learner as per Roll's suggestions (Roll et al., 2014b). This means that the robotic tutor does not need to be able to do many actions for the learner, as this would risk the learner becoming reliant on the robotic tutor.

The robot should behave in an appropriate way and not perform behaviours that could break the interaction or trust in the robotic tutor. Such as providing incorrect support or out of date information. The robotic tutor should not repeat itself and become repetitive or boring; in the study in section 3.6 the learners preferred the version that did not repeat a lot of detail. The robot should be engaging, initially this is easy to achieve due to the novelty effect of a robotic tutor and embodiment, however these effects can fade over time, so in longer term interactions the robot should use a memory of the learner. The robot should be able to carry out social and idle behaviours. Social behaviours aim to increase the immediacy (Szafir and Mutlu, 2012) of the robot to engage and motivate the learner.

4.6.2 Robotic tutor design

A fully autonomous Aldebaran Robotics NAO torso was used as the robotic tutor. The NAO was chosen as it could perform the anticipated behaviours/gestures, has good support for the creation of gestures and speech, and is robust. The robotic tutor offers behaviours that aim to give SRL support, motivational support, and domain support.

To enable this support the scenario manager and the pedagogical model can call predefined behaviours and speech to be carried out by the robot. In some cases the support requires key words or previously unseen text to be spoken by the robotic tutor so there is also the option for the scenario manager and the pedagogical model to pass this text for the robotic tutor to say. Examples of this are when the robot calls the learner by name, reiterates the objectives for a step, or highlights a keyword. The robotic tutor can also perform behaviours with the learning task and OLM interface. This is required for the robot to highlight a detail in the OLM or demonstrate how a tool works. The robotic tutor is able to carry out a selection of social and idle behaviours, which are described below, the set up of the interaction means that the learner is always stood in the same place so that the robot is able to look at where there learner is standing. The areas on the screen where the learner taps are also sent to the robotic tutor so it can look at the area where the learner taps.

The robot aims to be engaging and not repeat the exact same behaviour or speech repeatedly. To avoid repetition behaviour categories are made available which contain a number of alternative behaviours and speech that should offer support in the same way. For example, if the pedagogical model directs the robot to say something motivational, the pedagogical model requests the behaviour category for motivational statements, then the robotic tutor will choose between one of a number of motivational statements.

There are a number of mechanisms to ensure that the robot does not execute behaviour or speech that is out of date. Firstly, the pedagogical model tries not to request too many repeated behaviour categories from the robot in quick succession. In addition to this the screen is greyed out in the learning activity when the learner gives an answer, this helps prevent a lot of feedback being given in quick succession. As a final fail safe the robotic tutor also checks that a behaviour is still relevant before it executes it, this means that the robot should not give out of date support to the learner.

Overview of gestures and behaviours

The robotic tutor is able to carry out a range of different gestures that are put together to form the robotic tutor's behaviours. The robotic tutor is able to perform deictic gestures to point towards areas of interest in the learning activity, and also metaphoric gestures to represent the abstract concept of the skill meter, as these gestures from a tutor may be beneficial to learning (Kelly et al., 2008).

Social and idle behaviours The robot has a number of social and idle behaviours that aim to show that robot is aware of the learner without distracting the learner from the task. The robot uses subtle head nods, facial expressions, using LEDs in the robot's eyes, and body position to provide unobtrusive feedback on the learner's actions without unnecessarily disrupting the learner's train of thought (Johnson et al., 2000).

The robot's idle behaviours are subtle slow motions so that the robot does not remain static and appear unresponsive. The robot also has some basic contingent behaviours, where it will glance to where the learner is interacting with the activity similar to those used in the EMOTE project (Jones et al., 2015d).

Gazing at the learner is utilised by the robotic tutor when giving feedback. Szafir (Szafir and Mutlu, 2012) argues that non-verbal gestures such as these can be used as immediacy cues to improve the relationship with the robotic tutor and improve the tutors effectiveness. These behaviours aim to increase the immediacy of the robot to engage and motivate the learner (Szafir and Mutlu, 2012).

Motivational feedback As discussed later in section 5.2 there are robot behaviours to support the self-motivation of the learner, these include statements aimed to prompt goals, prompt reflection, and prompts to enjoy or value the learning process; these specific behaviours are listed in Table 4.2. These behaviours were based on utterances made by the teachers in section 3.7.

Table 4.2: Motivational statements

Pedagogical tactic	Example
Prompt to achieve mastery	Let's do it so that we can get 100%.
Prompt to reflect	What is it asking you to do this time?
Prompt to reflect	What could help you understand this problem?
Prompt to reflect	Look at the skill meter.
Prompt to reflect	You have got most of the questions correct for this activity correct.
Prompt to reflect	You can see here that you were pretty much right all of the time.
Prompt to enjoy	It can be enjoyable when you figure out hard problems.
Prompt to enjoy	It can be enjoyable when you make progress.
Prompt for importance	Do you think it is important to do well?
Prompt for how others may see learner	The teacher will think you are good if you do well.
Prompt for how others may see learner	The other children will think you are good if you do well.
Prompt to try	Just keep going and we can see if you are right or wrong.
Prompt to try	Use the skill meters to see if we got this right or wrong before!

Autonomous introduction The robot is able to introduce the task in a way that is motivating to the student. It is able to refer to the learner by name and give a tutorial for how the tools in the activity work. The robot is able to open and close the tools in the learning task interface as if a teacher was showing the learner the tools:

"Hi , today, we will practice your map reading skills. There are tools that can help you along the way in the bottom right of the screen. The map key will help you to understand what symbols on the map mean. The Compass tool will show the compass on the screen. It can help you to find the way. The Distance tool allows you to measure the distance between two points on the map. On the left you can see the skill meters, you can click on these to see evidence. On the left you can choose different activities at any time you like. We will start on Cardinal Directions. Please begin.".

Domain support The UCD studies have provided specific examples that were used to develop robot behaviours. In combining the experience derived from the UCD studies with a comprehensive literature review of tactics used by teachers during learning activities, a list of pedagogical tactics has been generated that the robotic tutor can use to interact with, scaffold SRL skills, motivate students, and provide domain assistance in their learning process. This is similar to the approach that was used in the EMOTE project to design the behaviours for an empathic robotic tutor (Jones et al., 2015d). On the basis of recordings made in the earlier studies, particularly the study described in section 3.7, concrete examples of utterances and behaviours have been collected that could be implemented in the robotic tutor. There are multiple behaviours for each tactic meaning that the robotic tutor can use the same pedagogical tactic in many different ways, giving it a dynamic and non-repetitive behaviour.

The robotic tutor in the study described in study 6 (section 6.3) uses this domain support. A subset of the categories of pedagogical tactics used on the EMOTE project (Jones et al., 2015d) has been used, these are re-question, keyword, pump, hint, and almost feedback. Domain support may be provided when the learner gives an incorrect answer (Figure 5.4) or the learner fails to give an answer before a timeout (Figure 5.5).

Table 4.3: Pump examples

Competency	Example
Direction	So which direction could that be?
Direction	Which direction should we go?
Distance	So how far is that distance?
Symbol	What could the symbol look like?
Symbol	Can you see the symbol?
Symbol	Can you identify this symbol?

The robot gives hints or other prompts for strategies that may prompt help-seeking to encourage the learner to use the tools at their disposal to solve the problem themselves (Roll et al., 2011). Examples are shown in Table 4.4.

Table 4.4: Hint examples

Competency	Example
Direction	Think about the cardinal points to discover that direction.
Direction	Consider what we said about the cardinal points to help you discover this one.
Distance	Try a different distance.
Distance	Can we measure the distance?
Symbol	If you are not certain what the symbol looks like on the map, we can check
Symbol	You can try the map key.

The robot provides tailored almost statements where the robot offers encouragement to keep the student motivated and to keep trying to make progress in the activity. Examples are shown in Table 4.5.

Table 4.5: Almost examples

Competency	Example
Direction	You're on the right track, but you are slightly off the direction you needed to go.
Direction	Almost!
Distance	Almost!
Distance	Very close.
Distance	Not quite the correct distance.
Symbol	You are really close.
Symbol	Try another symbol!

SRL scaffolding The robotic tutor in both section 6.2 and section 6.3 offers SRL scaffolding support as developed in section 5.2. The robotic behaviours to support the scaffolding are implemented by having the robotic tutor gesturing at the OLM and tools in the activity.

4.6.3 Robotic tutor implementation

The robotic tutor is connected to the Java module that runs in the same web server as the scenario manager, domain model, learner model, and pedagogical model. When the Java module starts up it creates a session that connects to the NAO robot over a local network connection using the NAO robots Java SDK and API[1].

The API exposes the robot's ALBehaviorManager[2] service that allows the Java module to start, stop, and get information about previously created behaviours on the robot. The process of recording gestures and behaviours is detailed below in the 'NAO behaviour implementation' section. The API also exposes ALTextToSpeech[3]

[1] http://doc.aldebaran.com/2–1/dev/java/index_java.html
[2] http://doc.aldebaran.com/2–1/naoqi/core/albehaviormanager.html?highlight=albehaviormanager
[3] http://doc.aldebaran.com/2–1/naoqi/audio/altexttospeech.html

service that allows the Java module to send text to the robot's text-to-speech engine, the result of the synthesis is sent to the robot's loudspeakers.

The java module maintains a first in first out queue of behaviour requests to be executed by the robotic tutor. The scenario manager and the pedagogical model are able to add behaviour requests to this queue. There is a process that is continually running behaviours on the robot. When a behaviour finishes executing on the robotic tutor the process checks the queue to see if there are any behaviour requests in the queue. If there is a behaviour request then the processes checks to see if the behaviour request is still valid to be executed (i.e. if it still applies to the step of the activity; was not requested too long ago). If the behaviour request is still valid then it will execute the behaviour and speech in the behaviour request on the robot and wait until it has finished before checking the queue again. If there are no behaviour request in the queue then the robot will perform an idle behaviour.

NAO robot hardware

NAO is a stationary humanoid robot. It is 307mm high, 275mm deep, 311mm wide, and weighs 2.2kg, this means that it does not pose any danger to the children. The head has 2 degrees of freedom (DOF), meaning that it can look up and down and pivot left to right, this enables it to nod and gaze at the learner or the task. The arms have 5 DOF each which allows them to move around quite freely and perform quite expressive gestures and point to the learning task interface. The hands have 1 DOF each which allows them to open and close. The NAO's eyes have 8 full colour RGB LEDS which can be programmed in a way to make it look as if it is blinking. The position of the NAO motors and DOF are shown in the diagram Figure 4.12.

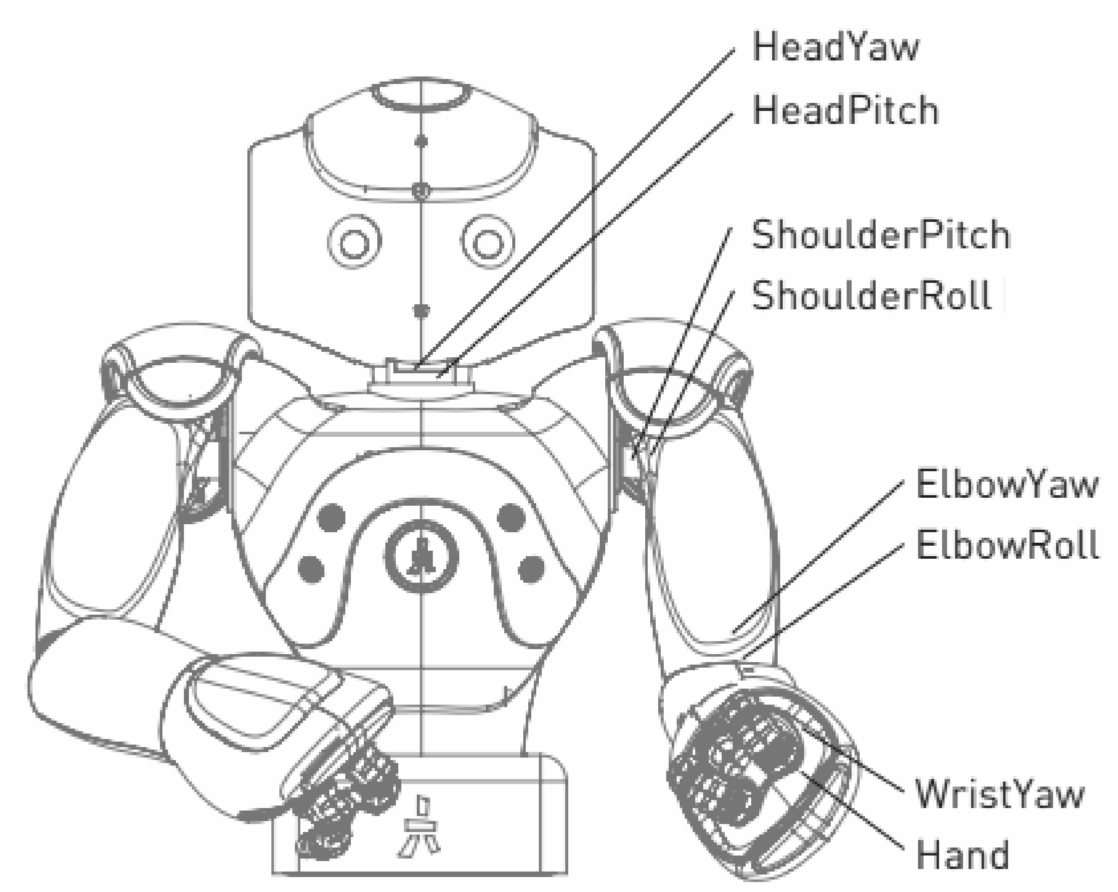

Figure 4.12: NAO torso degrees of freedom

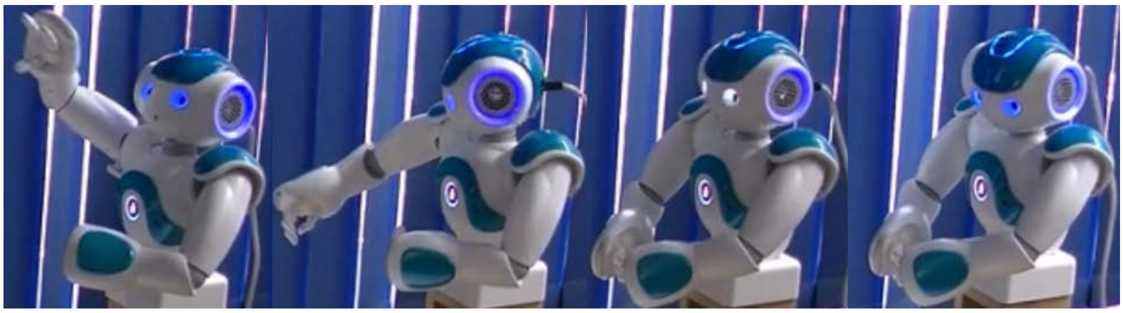

Figure 4.13: Examples of behaviours: greeting, pointing to OLM, nodding changing eye LEDs, gazing at learners touch

NAO behaviour implementation

The robotic tutors behaviours and gestures were created using the Choregraphe software available from the robot manufactures development portal[1]. Some examples are shown in Figure 4.13. The software allows the creation of behaviours and gestures in a similar way to a 3D animation, with a 3D model and the setting of the key frames of the animation, the robot will then automatically move between these key frames. The robot LEDs can also be set using the software. It is also possible to connect the robot to the software and physically set the robot into position to set the key frames, this is very useful as it is then quite simple to ensure that the robot accurately points to specific areas of the activity and is looking to where the learner should be. All of the behaviours created start and end with the robot in the same neutral position, this means that there are no large jumps in the robot position between one behaviour and another. The behaviours that were created are summarised in Table 4.6. It is possible to add speech to the behaviours in the Choregraphe software, however to keep the robotic tutor more flexible the speech has been implemented outside of Choregraphe. The creation of speech to accompany the behaviours is discussed in the next section.

NAO speech implementation

The NAO has a text-to-speech engine, the result of the synthesis is sent to the robot's loudspeakers. It is possible to change the parameters of the voice, however the default robotic sounding voice was used as it is clear and suits the robot embodiment. The text-to-speech engine does struggle to synthesise with some word and phrases clearly, so it was important to test all of the speech that the robotic tutor was to say. If needed it is possible to add pauses to the text so that the speech is clearer. It can also help to spell words differently so that the are pronounced more clearly, for example changing 'tools' to 'teuells' made the pronunciation much clearer.

[1]https://community.ald.softbankrobotics.com/

Table 4.6: Robotic tutor behaviour table

Behaviour	Description
Greeting	Wave and gaze at learner, idle motions
Neutral	A neutral pose gazing at learner
Idle	Move head and arms slightly from the neutral pose
Correct	Gaze at learner, nod head, positive beeping noise
Incorrect	Gaze at learner, shake head, sympathetic beeping noise
Decrease	Decreasing gesture
Increase	Increasing gesture
No change	No change gesture
Direction tutorial	Point at direction tool, open tool, gesture at compass
Distance tutorial	Point at distance tool, open tool, point at stating point, point at ending point
Symbol tutorial	Point at symbol tool, point at map key
Drag map symbol tutorial	Point at symbols on screen, mimic dragging gesture towards other area on screen
Explanation of OLM skill meter low value	Behaviour used by robotic tutor in section 3.6. If the competency decreases due to an incorrect answer or has stayed the same due to the lowest skill level
Explanation of OLM skill meter high value	Behaviour used by robotic tutor in section 3.6. If the competency has increased due to a quick answer or stayed the same due to the maximum skill level being reached
Explanation of OLM skill meter middle value	Behaviour used by robotic tutor in section 3.6. If the competency increases or stayed the same based on an answer that is correct but not given quickly
Point at OLM evidence	Point toward evidence area OLM while an OLM skill meter is expanded
Step objective	Point towards learning task interface objective area
Gesture at table	Point towards the centre of the touchscreen
Point to self	Gesture towards the robotic tutor
Point to learner	Gesture towards the learner
Gaze table bottom left	Gaze at the table
Gaze table bottom right	Gaze at the table
Gaze table top left	Gaze at the table
Gaze table top right	Gaze at the table

Behaviour and speech execution

Behaviours and speech are executed based on a behaviour request by the scenario manager or pedagogical model. The behaviour request can be explicit with the exact behaviour and speech having been specified in the request. This is done in the case where the robotic tutor is asked to say the learner's name, an objective of a step from the scenario script, or to say a keyword from an activity step.

Alternatively, a behaviour category can be specified. A behaviour category contains a collection of predefined behaviours and speech that are designed to offer the same support. A behaviour category is specified and one of the predefined behaviours and speech is selected at random to be executed. This allows the same support to be offered but in a less repetitive way. This approach is used for the pedagogical and motivation support shown in Table 4.3, Table 4.4, Table 4.5, and Table 4.2. The details of the behaviour categories, behaviours, and speech are stored in a file, this makes it simple to add more alternative behaviours and speech.

Social and idle behaviour implementation.

The robot's idle behaviours are subtle slow motions so that the robot does not appear to be static or unresponsive. The robot also has some basic contingent behaviours, where it will glance to where the learner is interacting with the activity similar to those used in the EMOTE project (Jones et al., 2015d). To support this the scenario manager records the last item or area that the learner interacted with in the learning task interface in the scenario state. When the robotic tutor performs an idle behaviour it is able to access where the learner last touched and how long ago the touch happened, if the touch was in the previous second the robots gaze would be directed to that general area by choosing the appropriate gaze behaviour. Otherwise the robot will perform a random idle motion which will include the slight adjustment of the robots head and arm positions from the neutral pose.

Robot synchronisation with the learning task and OLM interface

Some of the behaviours described above require the robotic tutor behaviour to synchronise with updates to the learning task or the OLM interface. This includes the tool tutorial behaviours where the tool should become activated as the robot gestures towards it, or when the robot gestures towards the OLM detail and a skill meter should expand. This is achieved by the behaviour placing a learning task interface update in a queue. The learning task interface polls this queue regularly and updates the learning task interface according to the behaviour requirements.

4.7 Summary of tutoring system development

In this chapter the design of the learning scenario that can support the demonstration and development of SRL skills has been described. The design has taken into account the findings from the UCD studies performed in chapter 3 and linked this with the latest research on learning scenarios that support the development of SRL skills. The following chapter explores how a tutor can use such a learning scenario as a basis to support a learner developing SRL skills.

CHAPTER 5

A COMPUTATIONAL APPROACH TO ADAPTIVELY SCAFFOLD SRL

This chapter discusses in detail the computational approach for scaffolding SRL skills that is used by the fully autonomous robotic tutor. The scaffolding is based on section 3.7 which investigates how experienced teachers scaffold SRL within the learning scenario and the background theorysubsection 2.3.2. This section describes how this computational model enables personalised adaptation to the learner to promote good SRL behaviours. A computational model is simply a model that can be run as a program on a computer.

- In section 5.1 the specification for the SRL scaffolding is presented, this is based upon theories for scaffolding SRL and how these link with the observations from the previous UCD studies. Events and their related underlying processes have been identified and used to create a computational model of SRL in the next section.

- In section 5.2 the model of how an ideal student with high level SRL skills would interact with the learning scenario is described. When a learner deviates from the ideal model the robotic tutor can adaptively scaffold the learner to more closely follow the ideal model. This has enabled the creation a computational model to enable personalised adaptation to the learner to promote good SRL behaviours.

Crucially, this model can be used to determine when and what a robot should do to support SRL skills in an HRI. The model is evaluated in chapter 6.

5.1 Specification for SRL scaffolding

This section will discuss some of the theories for scaffolding SRL and link them with the observations from the previous UCD studies. Both the UCD studies and theory presented below are used to design the computational model of SRL that is described in the next section. It is important to consider theoretical aspects of SRL so that a systematic study of scaffolding SRL can take place (Winters et al., 2008; Kitsantas, 2013). By looking at theory one can understand the factors that can affect SRL as a whole, ensuring that critical factors such as motivation (Kitsantas, 2013) are not overlooked. Theory can also be used to help define an operational definition of SRL in this context, this is beneficial over a vague or general definition as it helps to build the computation model of SRL and also evaluate the impact of scaffolding on SRL.

It is clear from the initial interviews in study 1 (section 3.4), mock-up study (section 3.5), and the previously described study (section 3.7), that the teachers continually provide feedback to the learners throughout the activity. This type of continuous feedback, designed to modify thinking or behaviour while learning is taking place, is called formative feedback (Shute, 2008). Shute (Shute, 2008), suggests that to be most effective the feedback needs to: be adapted to the learner so that it is appropriate; given at a time that the learner can use it; and be delivered to a learner who is motivated to use the feedback. This section will consider how SRL feedback or scaffolding can be provided to best effect as a form of formative feedback.

As previously discussed in section 2.3 learners do not always engage in the SRL process and/or use their SRL skills effectively. This could be due to a number of reasons: the student may not have sufficiently developed that skill; they maybe unable to apply it to the environment; they may not realise they should be using their SRL skills; or they may not be motivated to engage the SRL skills. From the previous studies there are examples of how teachers interact with the learner to motivate and scaffold SRL skills and attempt to overcome these difficulties.

The teacher was supported in the scaffolding of SRL skills with the learning scenario itself, as an effective basis for SRL skill development. The development of the learning task is described in section 4.2. The key points from theory on SRL tools is briefly reiterated here. Placing SRL tools within the learning scenario may prompt the learner to use the skills they already have. Researchers argue that without such tools or an environment designed to promote SRL skills, the development of SRL skills is unlikely (Barnard-Brak et al., 2010; Winters et al., 2008; Kitsantas, 2013). How teachers are able to use the tools in the scaffolding of SRL skills as it relates to key SRL processes will be discussed later in this section.

From the interaction between the learner and the teacher it can be seen that one of the most important aspects of scaffolding SRL is the social support through communication and collaboration. Even with access to tools students may not use the tools or engage SRL processes (Kitsantas, 2013; Winters et al., 2008). Students are more likely to engage in planning, monitoring, and strategy processes when provided with scaffolding (Kitsantas, 2013; Winters et al., 2008). This highlights the important aspect of social support in tool use. The impact of collaboration and communication has previously been investigated with education technologies and is beneficial as it can help students monitor their learning and increase understanding through on-line discussion (Järvelä et al., 2007; Kitsantas, 2013). Within the realm of OLM research, when a learner negotiates their learner model this can lead to the learner becoming more engaged, more reflective, and develop self-assessment skills (Kerly, 2009).

In subsection 2.3.3 it is discussed how important it can be for a learner to have

SRL skills demonstrated. In both section 3.5 and Study 4: UCD teacher study (section 3.7) teachers were observed initially demonstrating good SRL processes and then support the learner in adopting these processes as the interaction progresses. Kitsantas (Kitsantas, 2013) discusses the processes proposed by Zimmerman (Zimmerman, 2000) in which self-regulation can be developed in a social interaction. The social interaction supports meta-cognitive and motivational aspects of learning (Kitsantas, 2013). The learner will move from an initial reliance on social support towards more self-sustained SRL (Kitsantas, 2013). Table 5.1 shows the process of developing and gaining higher levels of SRL skills that this system attempts to model and scaffold. This process is based on the "Development of Self-Regulation with Learning Technologies" (Kitsantas, 2013). The computational model should support the 4 levels of SRL development discussed in the previous section (Zimmerman, 2000; Kitsantas, 2013). These are observation, emulation, self-control and self-regulation.

The shift in focus from teaching to learning is very similar to the view of constructivism taken by Akhras (Akhras and Self, 2000) and DuBoulay (Du Boulay and Luckin, 2016). The four main properties of constructivism that can be supported in the learning scenario are: cumulativeness, constructiveness, self-regulatedness, and reflectiveness (Akhras and Self, 2000). Cumulativeness refers to when a learner revisits an entity or views the entity in a different context in the interaction (Akhras and Self, 2000; Du Boulay and Luckin, 2016). Constructiveness refers to when the learning experience can be related back to the learner's existing knowledge (Akhras and Self, 2000; Du Boulay and Luckin, 2016). Self-regulatedness refers to a learner evaluating the outcomes of their earlier actions with a view to guiding what they do next (Akhras and Self, 2000; Du Boulay and Luckin, 2016). Reflectiveness refers to the learner engaging in reflective activities on earlier episodes in that interaction (Akhras and Self, 2000; Du Boulay and Luckin, 2016).

The teachers in study 2 (section 3.5) and study 4 (section 3.7) try to use an

Table 5.1: Process of development of SRL skills - shows the process of developing and gaining higher levels of SRL skills

Levels of Regulation	Description	Performance Indices	Example
Observation	Learners are shown the ideal steps, skills, and strategies.	Learner engages with OLM. Learner engages with learning scenario and robot.	Engagement with the robot. Engagement with activity. Learner follows instruction but takes little initiative.
Emulation	Learner is asked to emulate the ideal model.	Learner adopts domain strategies of the tutor. Learner listens to feedback from robot.	Learner taking lead. Copies the robot, but may not know why. Learner uses tools. May use tools when not needed.
Self-control	Learner moves beyond emulation and tries to master the steps, skills, and strategies required. The learner should focus on *process goals* (i.e. where the learner masters the processes involved in the activity) rather than *outcome goals* (i.e. where the learner aims for high outcomes or scores). The importance of focusing on *process goals* before *outcome goals* is shown in previous research (Zimmerman and Kitsantas, 1997).	Learner using tools appropriately. Learner has good low task level skills. Learner aware of skills.	Learner takes more control in activity. May not be considering bigger picture.
Self-regulation	Learner focuses on *outcome goals* after achieving mastery of the process in the previous phase.	Learner achieves mastery in the activity. Learner has high level awareness of ability.	Learner plans the activities to do to learn efficiently.

approach where they move from directing the learner in the use of SRL skills, to allowing the learner the space to self-regulate their own learning, e.g. by helping the learner to focus attention at the beginning of the session by reading instructions, to leaving the students to read instructions themselves as they encounter new activities.

The approach employed by the teachers in the studies is highly personalised to the learner's SRL skill levels, so that the learners are able to observe and emulate, before being encouraged to exercise self-control and self-regulation. VanLehn (VanLehn, 2011) highlights research that suggests that human tutoring is effective because the human tutor can accurately assess a student's competence and misunderstandings, give appropriate personalised feedback, assist with personalised task selection, provide learning strategies, allow the learner more control in the learning scenario, and provide motivation in a scaffolded way. Indeed, the importance of personalisation is discussed in section 2.1.2 and subsection 2.2.3 in relation to social robotics in education.

In study 4 (section 3.7) it was possible to match observations of both the teachers and learners with Zimmerman's cyclical SRL phases and sub-process (Zimmerman, 2008):

Self-reflection phase. In section 3.7 it was observed that teachers prompt the learner to self-reflect on their developing skills, attribute cause for changes in the model to the learner's performance, and also show satisfaction as the competencies increase. By encouraging learners to use the OLM as an assessment tool, the teacher is encouraging the learner to monitor their own learning (Dabbagh and Kitsantas, 2005). As described in subsection 4.4.3 an inspectable OLM is provided at all times in the activity. One of the aims of opening the learner model to the learner is to help promote reflection on the part of the learner; to facilitate their planning and decision-making; and raise their awareness of their understanding or their developing skills (Bull and Kay, 2010). Thus, the OLM can be seen as a form of scaffolding for cognitive and meta-cognitive processes, with a particular focus on supporting and developing self-regulation. The studies have shown that the teachers can scaffold the use of the OLM. This approach to supporting the learner can be very light or can be more closely guided. Sometimes the teacher might use the OLM to highlight the general progress of the students, at other times the learner may be supported to inspect the OLM in more detail and look at specific areas of weakness or strength. Notably, the teachers adapt to the goals of the interaction and the learner's current learning needs. The OLM was used by the teachers to keep the learner motivated. Thus, the model should support the learner to reflect on their learning. It should prompt them to make use of the OLM. It should make the learner reflect on the progress that they have made in their learning. The learner should feel satisfaction with their learning progress. Self-regulated learners should self-evaluate frequently and objectively (Kitsantas, 2013; Zimmerman, 2008). Reflecting on causal attributions for success and failures are important to success in learning (Kitsantas, 2013; Schunk, 1994).

Forethought phase. It was observed that the teachers in the studies build upon the learner's awareness of their developing skills to help set goals and strategies. Self-regulated learners should be able to set specific goals and plan how to achieve them (Kitsantas, 2013). This goal of goal setting and planning was assisted by providing course planning, sequencing, and scheduling tools. This takes the form of an activity menu where each activity shows the competencies that can be practised. By having the ability to plan, schedule, and sequence activities, the learner is supported in self-monitoring and help seeking (Dabbagh and Kitsantas, 2005; Kitsantas, 2013). It was also seen that the teachers used the OLM and the activity menu to prompt the learner to think about which activity to undertake. Indeed it has been seen that by providing students access to an OLM they can use it to select appropriate problems which allows them to learn more effectively (Mitrovic, 2007).

In addition to the learning sequence it is important for learners to have the appropriate types of goals for their state of development; process goals earlier on and then outcome goals when they have developed the skills required, e.g. teachers would encourage students to work in the more simple activities until they are proficient, then work up to the more advanced activities. This is in line with the theory of development of SRL as discussed above (Zimmerman, 2000; Kitsantas, 2013). The model should prompt the learner to consider process goals first and then move towards mastery goals. It should prompt the learner to reflect and to choose an appropriate sequence of activities in the learning scenario.

Also very important in the forethought phase of SRL is self-motivation. Self-motivation is made up of two factors: one is interest in the activity and the other is self-efficacy or self-belief that the learner can accomplish the task. Learners with high SRL skills report higher self-efficacy beliefs (Kitsantas, 2013). High levels of self-efficacy beliefs are correlated with learning performance (Kitsantas, 2013; Bandura, 1997; Zimmerman and Kitsantas, 2005). The studies saw examples where the teachers would try to build the learners' self-efficacy by highlighting how well they were doing. As mentioned above, the teachers used the OLM to do this as part of the support for the self-reflection phase.

Performance phase. The teachers also used the OLM as a basis for self-control by prompting task strategies and attention focusing. In this phase the teachers also sought to prompt self-observation and meta-cognitive monitoring. The OLM is ideal to support and prompt the learner to self-monitor, as it makes it easier for the learner to track progress against the competencies required for learning. Being able to self-observe and track aspects of learning is very effective in academic learning (Kitsantas, 2013, 2002; Kitsantas and Zimmerman, 2006). The aim is to support self-observation and monitoring by providing cognitive tools. This approach provides cognitive tools in the environment that help students offload cognitive processes associated with the task (Roll et al., 2014b; Jonassen, 1992). An example of a cognitive tool is a tool that can help students make hypotheses and test them as in the Crystal Island learning scenario (Shores et al., 2011). Another example is an electronic notebook CoNoteS2 (Hadwin and Winne, 2001) that can help students understand tasks, create personal goals and plans, and review and track learning. It is thought that the use of these tools engages the learner in the task and makes them aware of the effectiveness of using these types of reflective thought processes (Jonassen, 1992). In the wind farm activity described in section 4.2.2 tools are provided for making hypotheses. In addition to this the OLM can be used by the learner to work in a trial and error way.

Access is provided to domain specific learning tools. The use of these tools can be scaffolded in a way that applies SRL skills to the specific domain strategies. A learner with high levels of SRL skills would choose appropriate task strategies to meet their goals (Dabbagh and Kitsantas, 2005). With the tutor able to demonstrate appropriate tool use to the learners, it is then hoped that the learner will be able to self-regulate the use of the domain tools available to them. Thus, the model should help the learner to use appropriate domain strategies and tools. It should prompt the learner to use the cognitive tools available to them in the form of the OLM and the tools in the later activities. The model should also help the learner to focus their attention.

5.1.1 Summary

In this section observations of how teachers use the OLM in this context is merged with theory and research that focuses on scaffolding SRL skills and its implications for broader academic learning. The result of this process has provided an observational and theoretical basis for the development and implementation of the computation model of SRL and the creation of a specification for how a social robotic tutor can most effectively support SRL.

5.2 Computational approach for adaptive SRL model

To support adaptive SRL scaffolding ideal model of SRL has been created for this learning context. This style of model tracing approach is recommended in other meta-cognitive tutoring systems, for example a meta-cognitive tutor that focuses on when a student should ask for help (Aleven et al., 2006).

The system as a whole, including the robot is designed to motivate the learner to employ and develop SRL skills. Based on the iterative UCD approach and review of the theoretical literature described in section 5.1, a computational approach has been developed for the adaptive SRL model. The model specifies how an ideal student with high level SRL skills would interact with the learning scenario. When a learner deviates from the ideal model the robotic tutor will adaptively scaffold the learner to more closely follow the ideal model. This pedagogical model comprises of a set of rules that determine behaviours of the robotic tutor. These rules have been based upon findings from user studies and literature review.

By following this approach the aim is to support scaffolding of SRL skills in a way that has been observed in the teachers in the studies, and is in line with the view of constructivism taken by Akhras (Akhras and Self, 2000) and DuBoulay (Du Boulay and Luckin, 2016), and the SRL training approach of Kitsantas (Kitsantas, 2013) and Zimmerman (Zimmerman, 2000). This is where the learner will move from an initial reliance on social support towards more self-sustained SRL. SRL processes take place at many levels, from low level performance through to high level planning. The model causes the robot to demonstrate the SRL processes that are needed by the learner at their current level of SRL skill. This may be in the form of highlighting SRL refection, SRL planning, or appropriate SRL domain strategies. In time the learner will start to emulate the behaviour prompted by the robotic tutor. It is hoped that the learner starts to internalise the SRL processes and gain more self-control. The robot keeps the learner motivated, supports process orientated goals and encourages the learner to achieve mastery.

The model also takes into account the SRL tools and the learning scenario and how these should be used to develop SRL skills through the different phases of SRL. The relevant guidelines from Bekker's DSD cards (Bekker and Antle, 2011) have also been included, these were created to make age specific information about children's developing cognitive, physical, social, and emotional abilities readily accessible for designers. The information in these cards is age specific and therefore assisted in ensuring that the ideal model of SRL was appropriate for the developmental age of the learners. The use of these cards is explained in section 4.2.1.The next section will now describe how the model can help scaffold the different phases of SRL.

5.2.1 Ideal model of SRL

This section describes the ideal model and how the learner might deviate from it. It also explored throughout how to scaffold and support the learner to better follow the model and limit these deviations. There is a diagram of the model in Figure 5.1. The phases of the SRL are shown in the diagram, with *SRL self-reflection phase* in brown boxes, *SRL forethought phase* in green boxes, and *SRL performance phase* in light blue boxes.

The learner starts by thinking about which activity they should undertake. This part of learning involves self-reflection, forethought, and performance. The learner must evaluate their own skills, set goals and motivate themselves, and then think about how they will be able to perform the activity. The aim is to scaffold SRL by prompting the learner to reflect on their skill levels and choose appropriate activities. At this stage they may deviate from the ideal model by not engaging SRL forethought skills and choosing an inappropriate activity that does not meet their learning goals. The robotic tutor support at this stage is detailed in section 5.2.2 and shown in the diagram (Figure 5.7). The robot can also offer support for SRL forethought and motivation with the introduction described in section 5.2.2 and shown in the diagram in Figure 5.2.

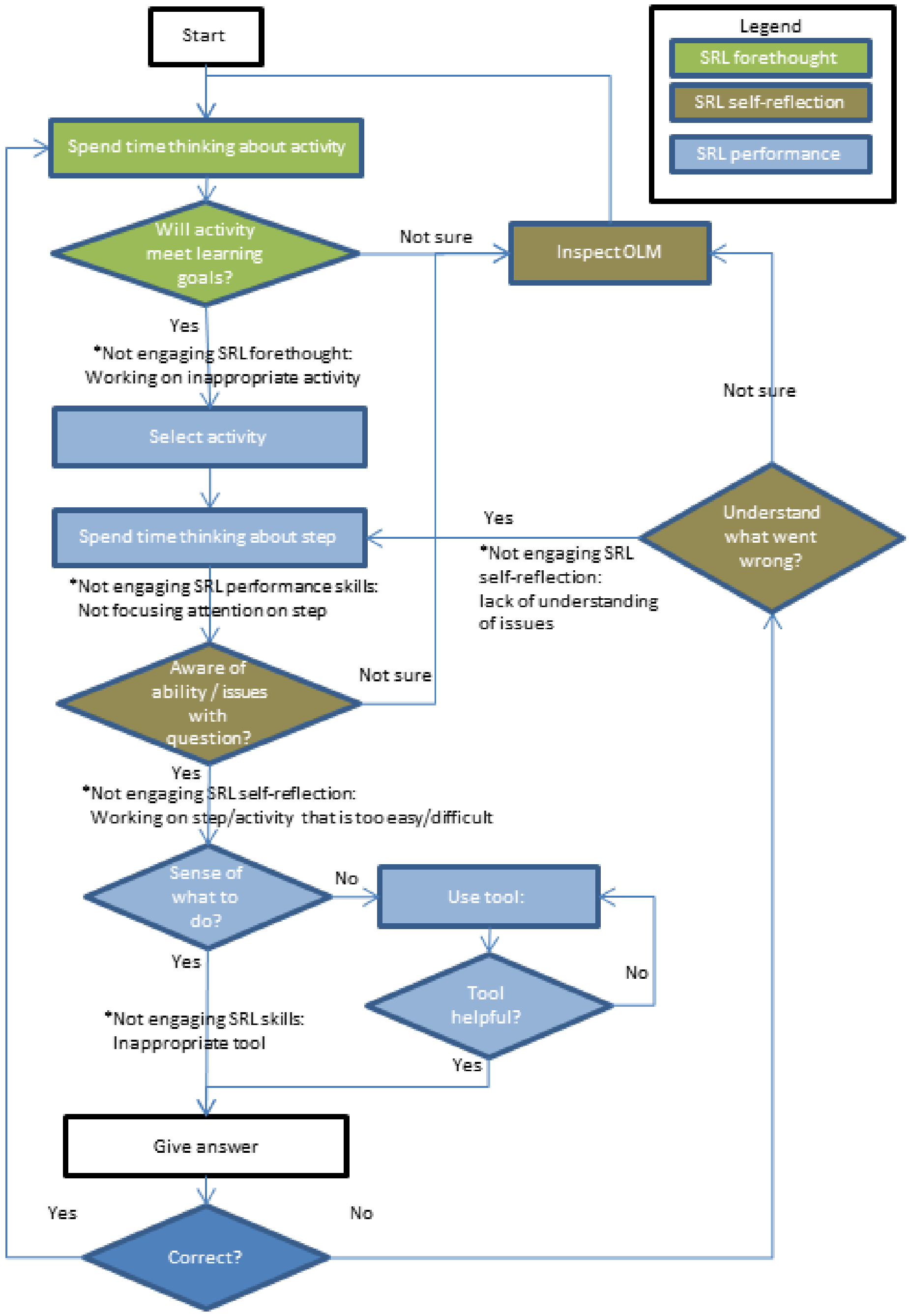

Figure 5.1: A model of ideal or desired SRL behaviour, * show where violations can occur

Once the activity is selected the learner should spend time thinking about the step. They must focus their attention and ensure that they understand the activity step, if it is an appropriate difficulty and if they have a sense of what to do. A deviation occurs here if the learner has not properly focused their attention and understood the step. The robotic tutor may support the learner by reading the step as teachers did in section 3.5 and section 3.7. If the learner has answered incorrectly the tutor can reiterate the step as detailed in section 5.2.2 and shown in Figure 5.4. The learner should also be able to self-reflect and self-assess their competency and knowledge as it applies to the step. There is a deviation if the learner is not aware of their weaknesses, the robot is able to support the learner by prompting them to use the OLM and highlighting where there may be issues as shown in Figure 5.4. At this point the learner can potentially choose another activity. If the learner attempts the step but is unsure of what to do, they can use the tools in that activity to help answer the problem. The robot can support the learner in appropriate tool use as shown in section 5.2.2 and shown in Figure 5.6.

If the learner is answering correctly then they can consider if they have mastered the activity. If the learner has entered a number of steps correctly and is confident then they should move on to a different or more difficult activity. A deviation at this point is continuing the task regardless of performance. The robotic tutor can support the learner here by prompting them to reflect on their competencies, knowledge, and their mastery of the activity and potentially moving on to harder activities as described in section 5.2.2 and shown in Figure 5.3.

If the learner answers incorrectly then they will need to self-reflect and understand what went wrong. Even from a guess it may be possible to understand what went wrong and adapt to fix this. At this point the learner may also wish to inspect the OLM to identify where they might have specific issues or misconception. A deviation of the model at this point is to get multiple incorrect answers without taking the time to reflect and understand the issue. In section 5.2.2 and Figure 5.4

it is shown how the robotic tutor can support with forethought, self-reflection, and performance by prompting the learner to use the OLM, prompts to use tools, to focus attention, and if that fails by offering domain support.

How to effectively scaffold and support the learner to better follow the ideal model and limit these deviations is the subject of the remainder of the chapter.

5.2.2 Fully autonomous robot behaviours

This section describes the fully autonomous robot behaviours designed to scaffold SRL skills of a learner and prompt them to adhere more closely to the ideal model described above. The UCD studies in chapter 3 and section 5.1 have provided insights into the practical requirements needed to create a believable interaction with a robotic tutor in the context of this research.

The feedback provided to the learner in this learning scenario is primarily given contemporaneously when the learner deviates from the ideal SRL model or when the learner requires some domain tutoring. This is based on observations of the teachers continually providing feedback to the learners in the activity in the mock-up study (section 3.5), and study 4 (section 3.7). This is also in line with the theory that formative feedback is most effective when provided at a time when a learner can make use of it (Shute, 2008).

This section describes a pedagogical model that attempts to understand when the learner deviates from the ideal model of SRL described in subsection 5.2.1 and prompts the learner to adhere more closely to it. In the diagrams listed below the various triggers for the pedagogical model in trying to asses when the learner deviates and the support offered by the robotic tutor to the learner to adopt SRL skills. The support provided by the robotic tutor is dependent on the learning task state, the learner model, and the learners' adherence to the ideal SRL model. In the diagrams listed below the support of the *SRL self-reflection phase* is highlighted in brown boxes, *SRL forethought phase* in green boxes, and *SRL performance phase* in light blue boxes. The deviation or triggers for evaluation are below, throughout the rest of this section the strategies and tactics that the robot employs in reaction to these triggers and the reasoning behind them are also explained:

- The start of the session summaries (Figure 5.2)
- Learner gives a correct answer (Figure 5.3)
- Learner gives an incorrect answer (Figure 5.4)
- Fails to give an answer before a timeout (Figure 5.5)
- Selects a tool (Figure 5.6)
- Inspects the activity menu (Figure 5.7)
- The end of the session wrap-up (Figure 5.8)

The diagrams can all be found in the section below. When one of these events occurs the system evaluates if the robot should execute a behaviour according the condition. For example, the "Let's keep going we have not covered everything" utterance may be triggered by a timeout, if the learner has not carried out an action for over 15 seconds, or by an answer attempt, but only if the learner has not mastered the activity, meaning they have not shown evidence of correctly answering each aspect of an activity.

Start of the session

To begin the robot introduces the task in a way that is motivating to the student, to encourage the learners to become excited about the learning process. From a meta-cognitive planning or forethought perspective it is important to reflect back on previous learning sessions. In study 6 (section 6.3) multiple sessions are analysed to provide a summary of the progress made in the previous sessions. Figure 5.2 effectively shows how this works in practice.

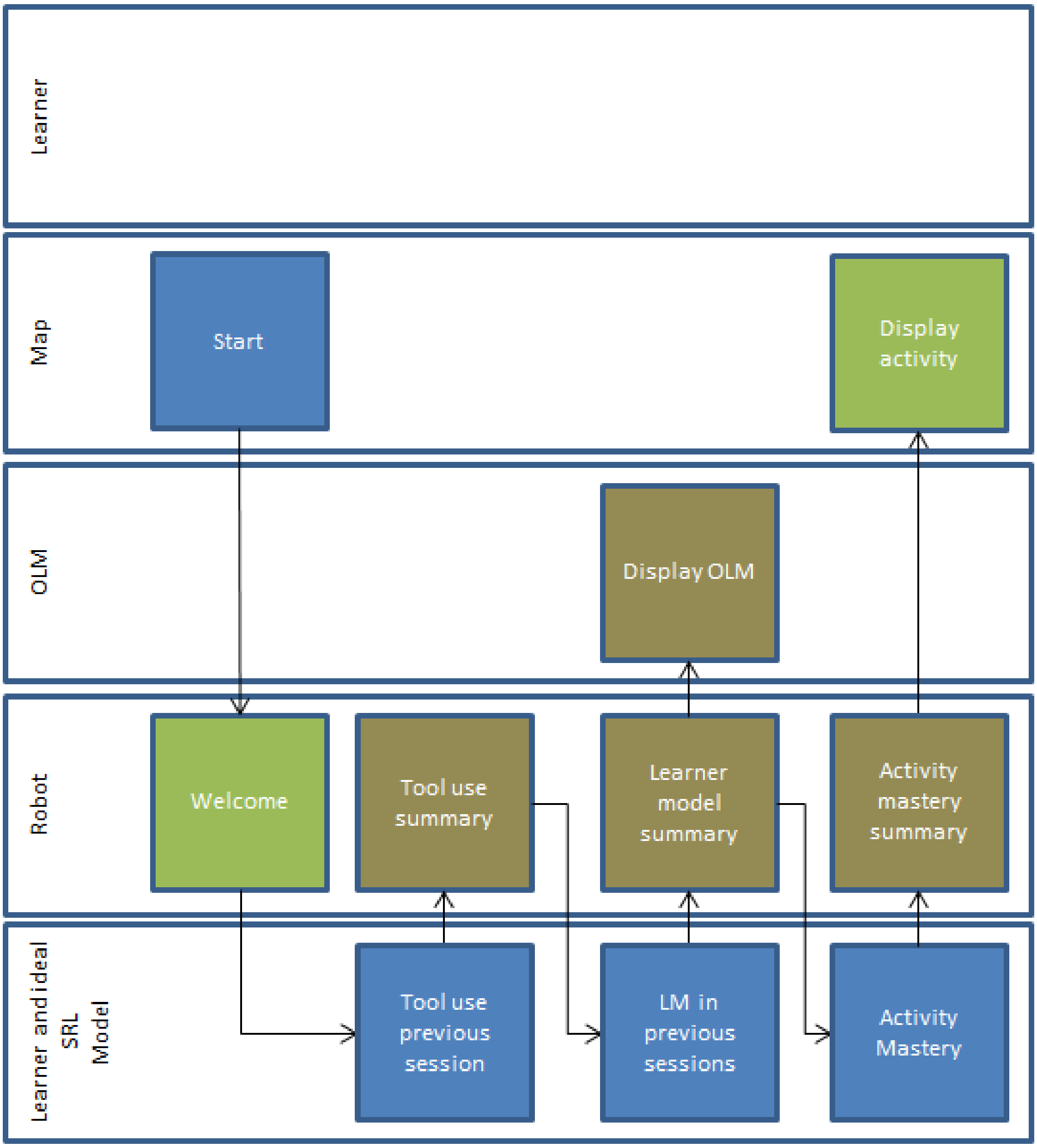

Figure 5.2: Robot behaviour at the start of the session

From discussions in chapter 3 it was identified that the robot could itself express the model content by giving a summary of relevant knowledge or competencies at the start of a session, effectively showing that the robot remembers the learner. The robot uses the learner model visualisations on the table top to highlight this information. This is exactly what the studies in section 3.7 show the teacher doing.

The *summary* at the start of a session is very similar to the *wrap-up* at the end of the previous session and the robot will also remind the learners of the tools and activities:

"Hi George! Good to see you again. You used the tools well but also when you did not really need to. On the left you can see the skill meters, you can click on these to see evidence. Last time you did really well at your distance and symbol skills. You could work on your direction skills. It looks like you mastered the distance in kilometres, distance in metres and cardinal directions activities last time and moved on to challenge yourself."

Correct answer

The robot gives positive beeps and noises when the learner is answering correctly (Figure 5.3).

The robot supports self-reflection and a level of forethought based on the learner giving a correct answer (Figure 5.3). The robot provides support based on the learner's mastery of the current activity and how this interacts with the ideal SRL model.

If the learner has answered all elements of the activity correctly and has a high level learner model for the competencies tested by the activity, then it is considered that the learner has mastered the activity; in this case the robot will prompt the learner to move on to another activity: *"Well done! It looks like you have mastered this. Shall we move on to another activity?"*, or *"Okay, do you think that was a bit easy for you?"*.

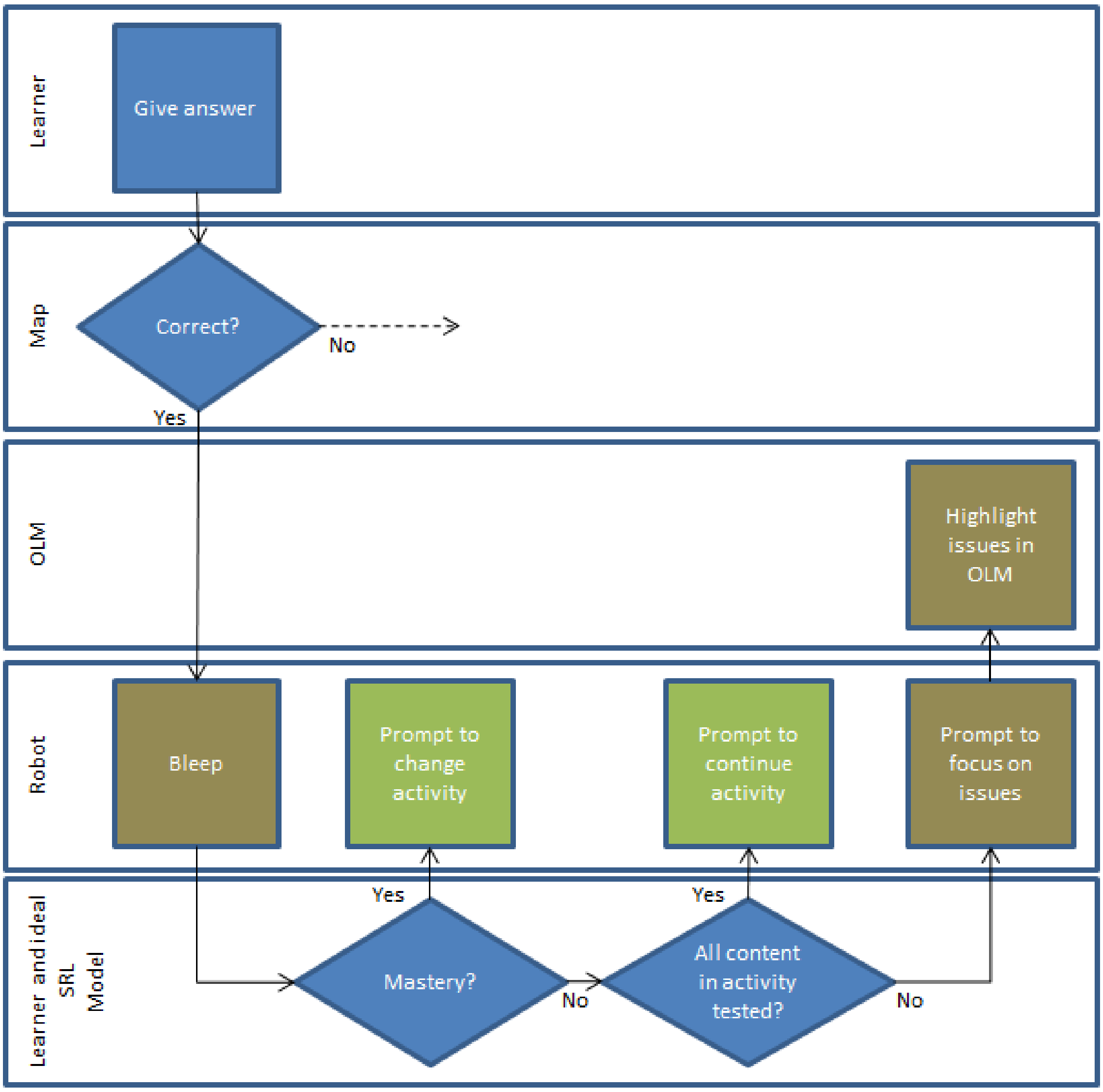

Figure 5.3: Robot response to learner providing a correct answer

If the learner has a high learner model level and is doing well, but has not shown evidence of mastering all of the elements they may be encouraged to continue with the activity to achieve mastery: *"Let us keep going, we have not covered everything yet."*.

Incorrect answer

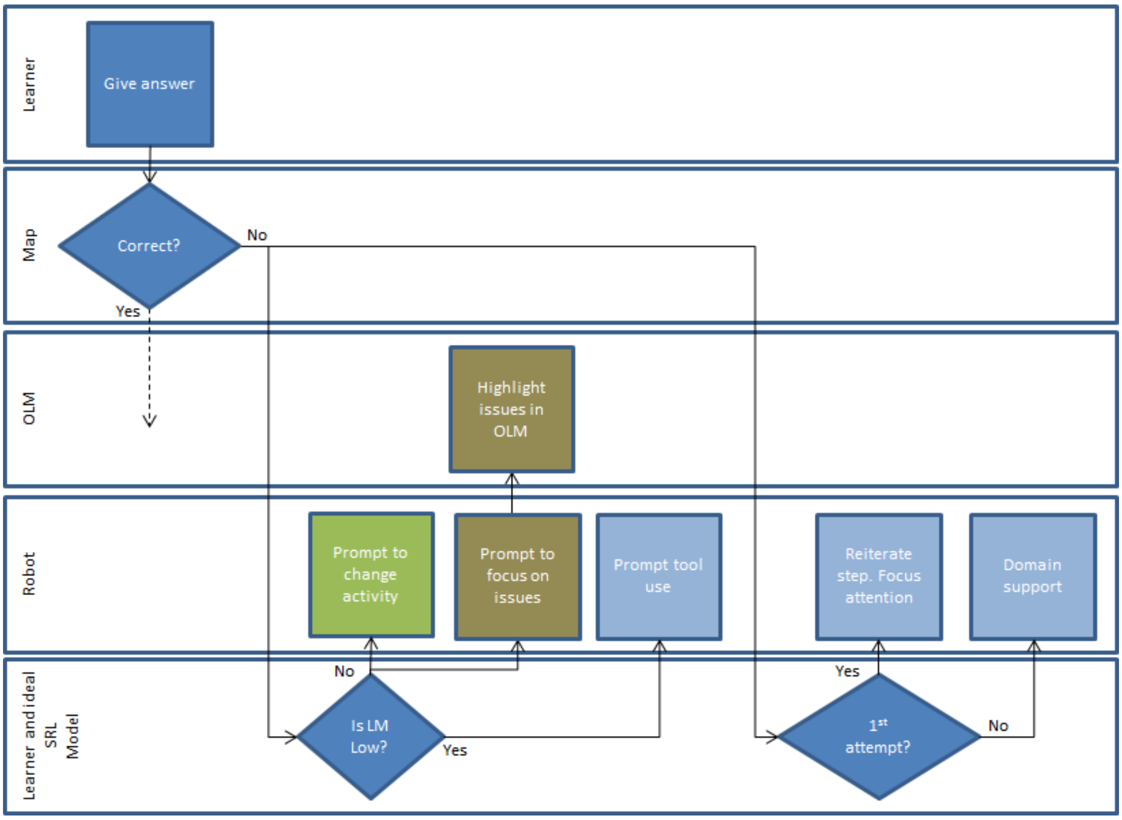

Figure 5.4: Robot response to learner providing an incorrect answer

The robot supports self-reflection and a level of forethought based on the learner giving an incorrect answer (Figure 5.4). The robot provides support based on the learner's mastery of the current activity and how this interacts with the ideal SRL model.

If the learner has elements of the activity that they have repeated issues with, then the robot will highlight these elements in the OLM. The robot can look and gesture towards particular features of the learner model. It can also gesture with its hands and arms to mirror the skill level. This support can be less guided with a prompt to look at the OLM (for the competency at a high level), e.g. *"How are your compass skills do you think?*, or the support can highlight a specific piece of knowledge by gesturing to the OLM, e.g *"Let us keep going, we need to focus on south-west"*, depending on the learner's current learning needs. It is hoped that the learner will reflect on this gap in knowledge or skill and will address this with appropriate SRL strategy.

To reiterate the points above, in the cases where the robot elects to provide support it first checks if there is any SRL support that can be offered e.g. if the learner model is low, then the robot may highlight aspects of the OLM to the learner to encourage reflection. However, at some point prompts to reflect may not be effective so it is important to guide the learner to a greater degree, in order to avoid the learner becoming demotivated. This is in line with recommendations from Bekker (Bekker and Antle, 2011) that problem solving can be supported through demonstrating a problem solving process for a child to follow; encouraging the learner to try different approaches; recognising when a learner is struggling; and in addition to this, supporting the learner's understanding of instructions. If the learner is still having difficulty following instructions the robot can help by breaking instructions down into simple steps.

The first pedagogical tactic used by teachers is to re-question (Graesser et al., 1999) the learner, this is simply to read the question out loud to ensure that the learner's attention is focused on the task at hand. This tactic was witnessed in all of the teacher studies.

The next most common piece of domain support is to simplify the task or break the problem into smaller pieces to try to make it more manageable. In this context keywords can be used. The learner model is used to identify which aspect of the question the learner is having the most difficulty with, and in the first case the robot states the most appropriate keyword related to the task.

If the learner is still making mistakes, the robot will either 'pump', 'hint', or provide 'motivational' or 'almost' feedback, the implementation details of this is discussed in section 4.6.2. Pumping the learner for more content, aims to encourage the learner to reflect and expose knowledge, or construct content by themselves (Graesser et al., 1999). Examples of this are shown in Table 4.3.

Timeout

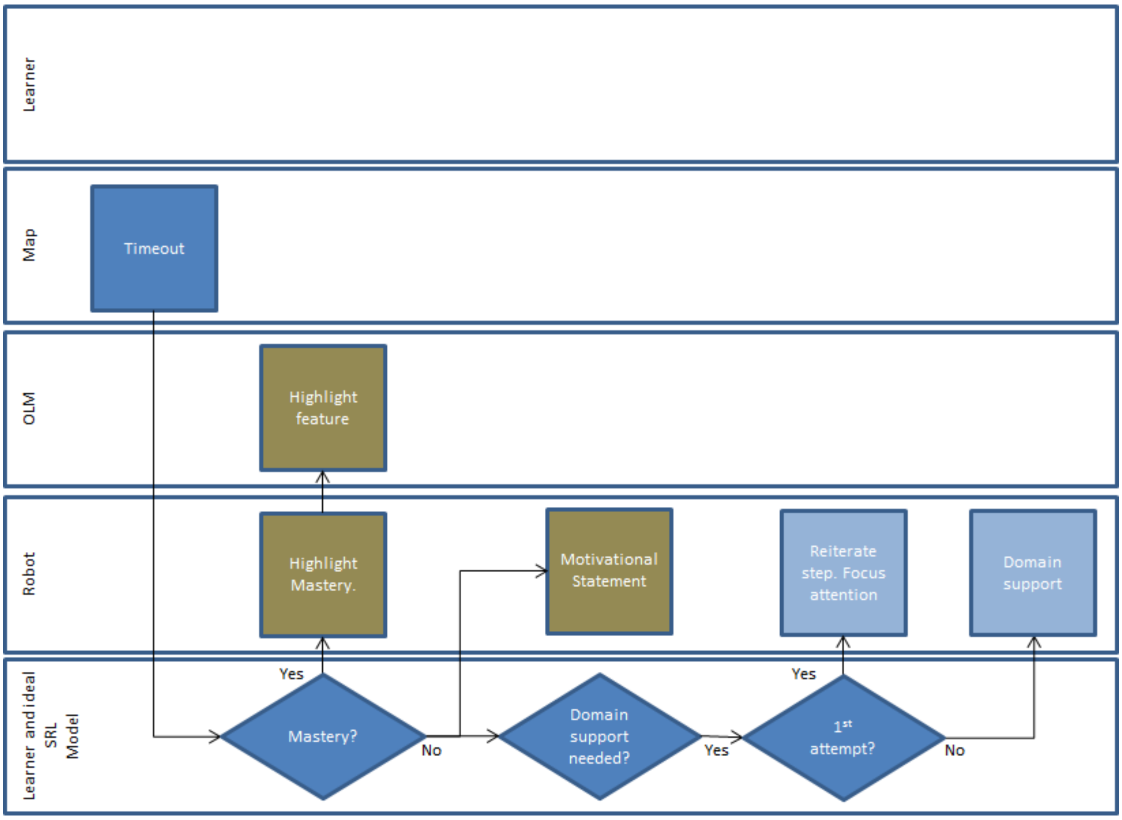

Figure 5.5: Robot response to timeout being reached

The support offered following a timeout event is similar to the support offered in the events of correct answer or incorrect answer. If the learner is doing well in the activity they may be prompted to move on. If the learner is experiencing difficulty in the task they will be offered domain support.

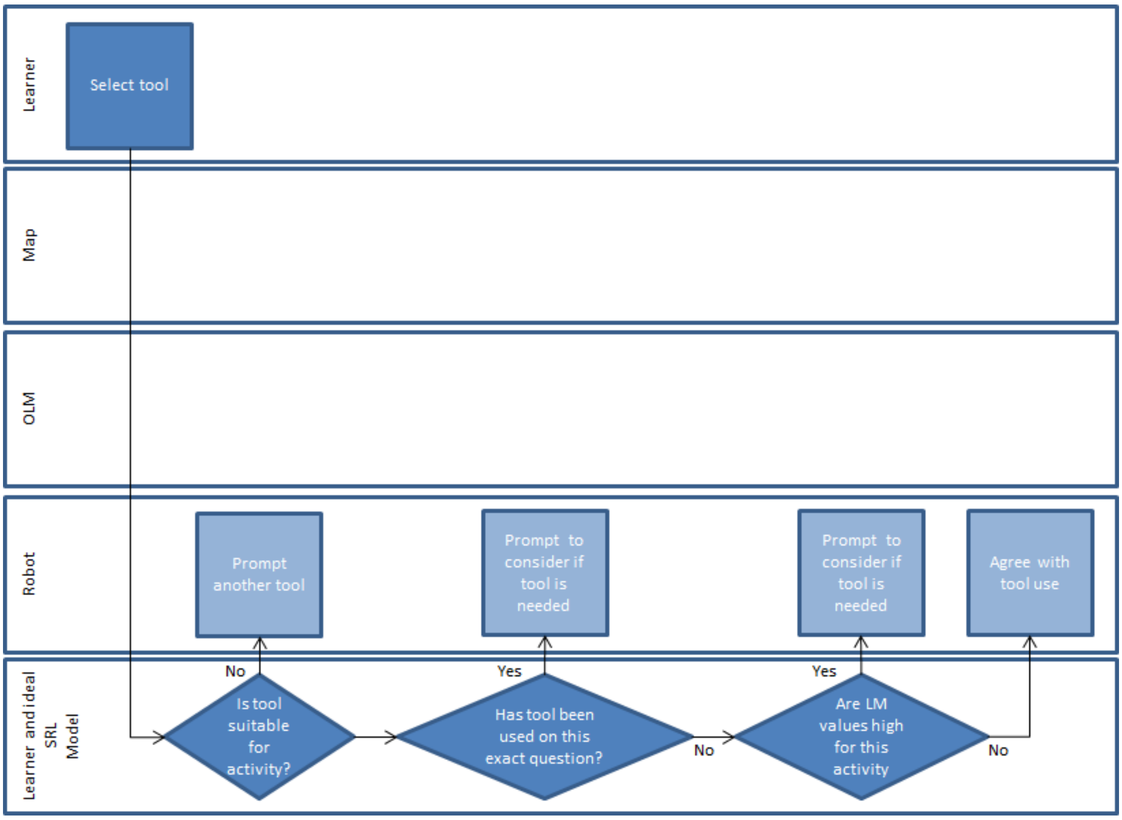

Figure 5.6: Robot response to learner selecting a tool

Tool selection

In addition to the high level suggestions for tool use provided to the learner in the summary and wrap-up, more detailed and low level support for appropriate tool use is also provided when the learner selects a tool (Figure 5.6). When the learner selects a tool the learner model and ideal model of SRL is used to determine if the use of the tool is appropriate or not. If the tool use is appropriate, i.e. the learner has a low learner model level or if they have made mistakes in which the tool can help then the robot may give positive feedback: *"This tool should help!"*. If the tool is irrelevant to the task at hand, then the learner would be prompted to use a different tool: *"Is there another tool that can help you?"*. If the learner has already shown mastery of an item of knowledge, then the robot will prompt the learner to reflect on that mastery: *"You got this type of question correct last time, do you still need the tool?"*. If the learner has shown mastery or a high level of skill in that area, then the robot will prompt the learner to reflect on that mastery: *"You have a good skill level for this task, do you still need the tool?"*.

The learner will only receive these prompts if they are breaking from the ideal model of tool use developed in section 5.2.

Open activity menu

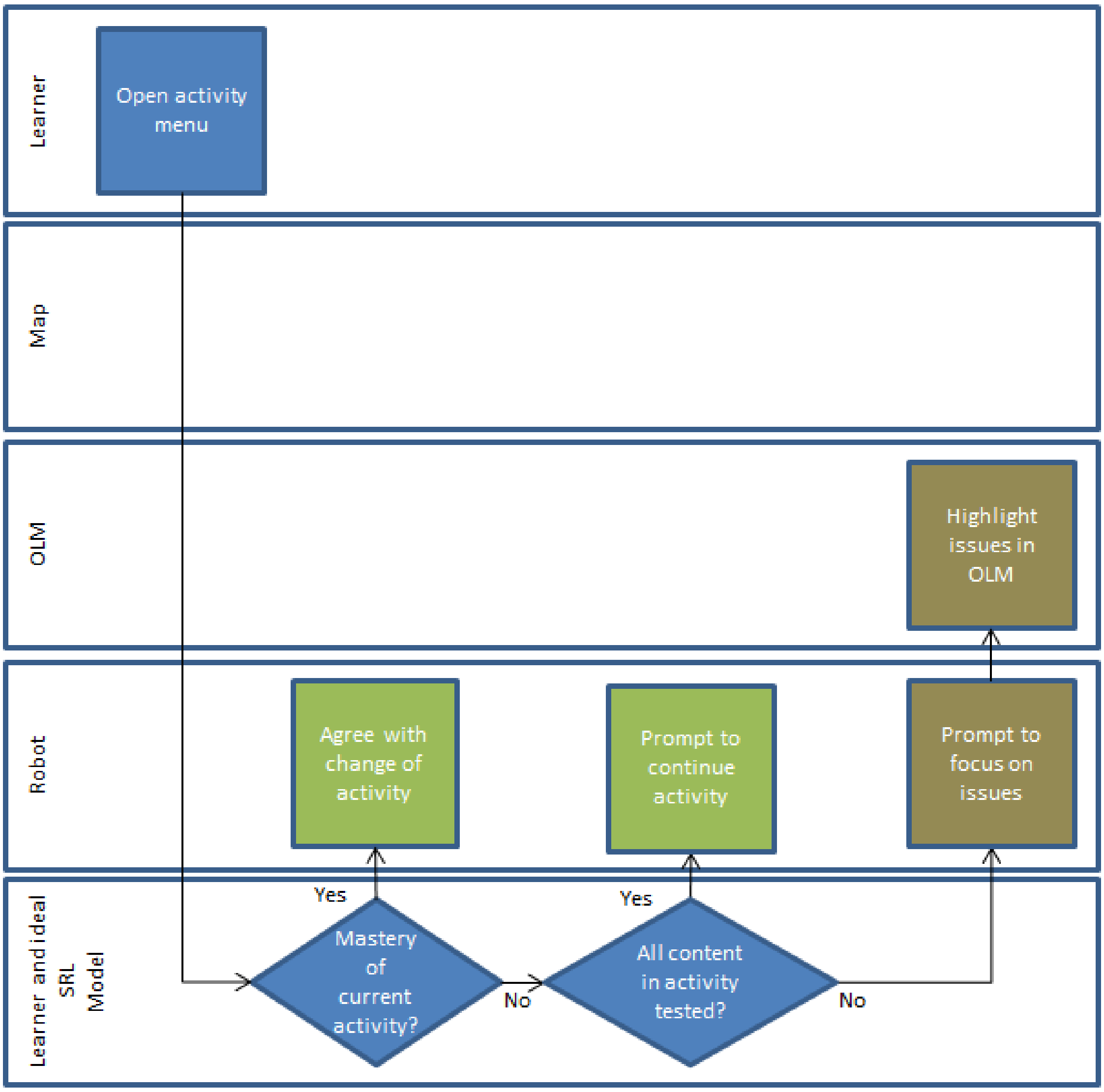

Figure 5.7: Robot response to learner inspection of the activity menu

The robot supports self-reflection and forethought based on the learner inspecting a different activity (Figure 5.7). If the learner has mastered the current activity the robot will offer positive feedback, otherwise the robot will prompt the learner to continue in the activity or focus on a specific item of knowledge.

End of session

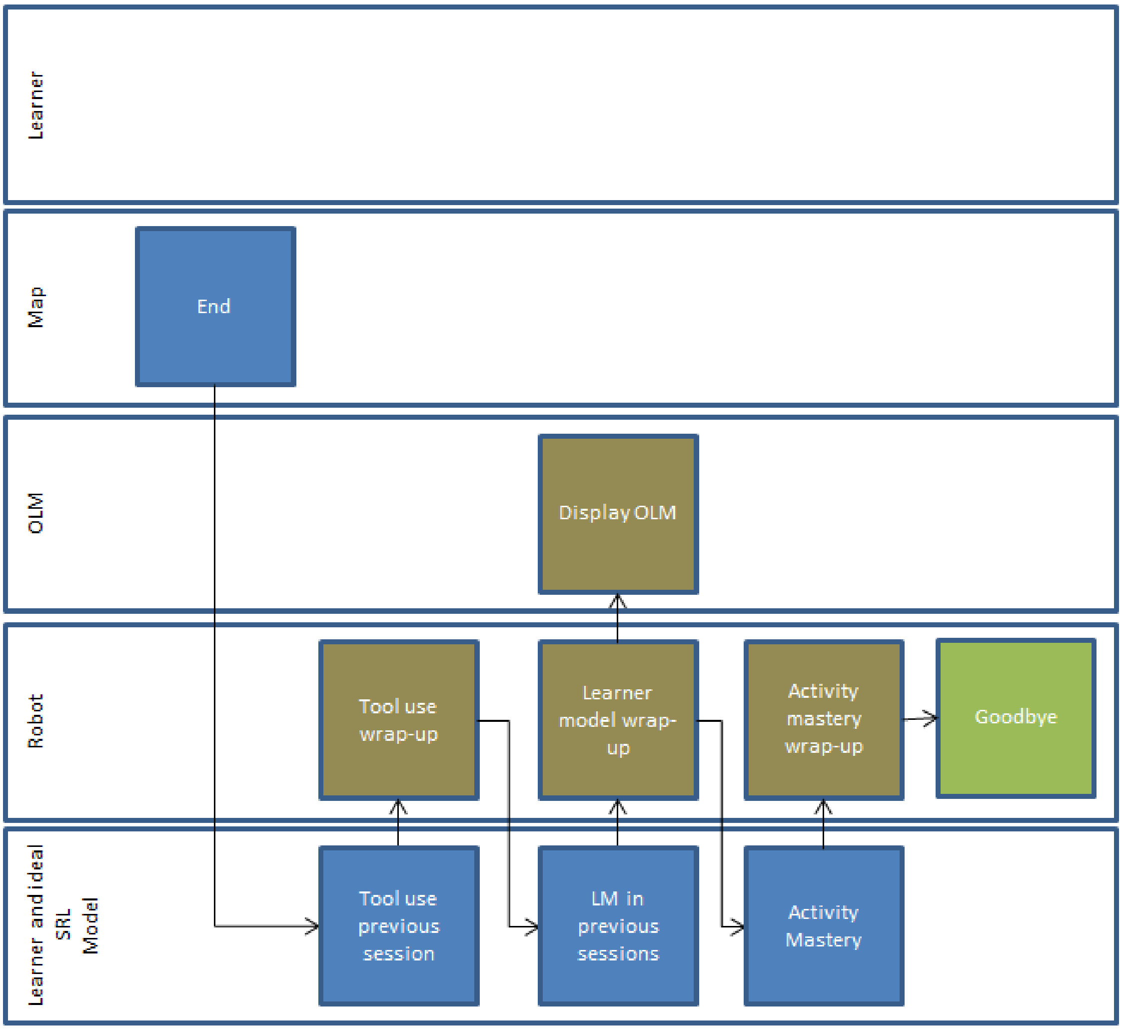

Figure 5.8: Robot behaviour at the end of the session

From a meta-cognitive planning or forethought perspective it is important to reflect back on the learning session that has just been completed, indeed teachers gave a wrap-up at the end of the session in section 3.7.

The *wrap-up* at the end of a session uses the learner model and model of SRL to help the learner to reflect on their tool use, improving skills and mastery of the activities and learning material. The learner is congratulated on completing the session and is then given a summary of their tool use in the session. The robot praises the learner's tool use if the learner has used the tools appropriately according to the ideal model of SRL. Appropriate tool use is when the learner mainly uses tools when they have a low learner model level in a skill or need to practice a skill. Inappropriate tool use is when the learner is using tools all of the time, even when they have already shown the ability to answer the question without the tool. In this case the learner is prompted to consider their tool use and to try and not use the tools when they are not required. It is also considered inappropriate tool use if the learner is not using tools when they are making mistakes and have a low learner model level. In this case the learner is encouraged to make use of the tools in the next session. The learner is also given a summary of their map reading skills as the robot gestures to the OLM and indicates the skills that have improved and the skills that require more work before the robot concludes by commenting on the activities the learner has mastered. It is hoped that this final step will provide the learner with a sense of achievement. This feedback is given at a high level so as to better support reflection around forethought and planning:

"Good Work Cai. You used the tools well but also when you did not really need to. You did really well at your distance skills. You could work on your direction and symbol skills. It looks like you mastered the cardinal directions, all map skills, activities and moved on to challenge yourself."

Transition from external support to self regulation

Due to the nature of the ideal model based approach, as a learner develops and shows SRL skills, the prompts from robot will become less frequent. In this way the model supports an initial reliance on social support towards but then allows a self-sustained SRL (Kitsantas, 2013).

Table 5.2: Robot behaviour to support SRL forethought phase

Robot Behaviour	Triggers
Summary of the progress made in the previous sessions	Start of session Figure 5.2
Positive beeps	Learner provides correct answer Figure 5.3
Suggesting goals, prompt reflection, or highlight importance of the learning process with statements from Table 4.2	Timeout reached Figure 5.5
Summary of the progress made in the session	End of session Figure 5.8

Support for SRL forethought phase

Table 5.2 shows the support offered for forethought; the reasoning behind which is described in this section. Giving a summary or wrap-up during a session aims to provide the learner with a sense of achievement and prompt them to think about their learning and how they might use the OLM information.

The robot also tries to motivate students when the user has not interacted with the activity for a set timeout period (Figure 5.5). It does this by *suggesting goals*, *prompting the learner to reflect* on the problem or their progress, or *highlighting the importance of the activity and learning process*. The possible statements are listed in Table 4.2.

Support for SRL self-reflection phase

Table 5.3 shows the support offered for self-reflection; the reasoning behind which is described in this section. Bekker (Bekker and Antle, 2011) recommends and highlights the importance of building the learner's self-esteem. This is achieved by encouraging a learner to use skills they have already developed to complete a new task; helping the learner recognise how certain skills can transfer to a variety of different activities; practising skills to complete a more complicated activity; helping the learner understand how specific skills relate to a more complicated activity;

Table 5.3: Robot behaviour to support self-reflection phase

Robot behaviour	Triggers
Prompt the learner to reflect and move on to another activity	High level of mastery (Figure 5.3) and (Figure 5.7)
Encourage the learner to continue with the activity	Mastery not achieved (Figure 5.3) or (Figure 5.4)
Prompt to reflect about a competency at a high level	Learner model is low (Figure 5.4) or (Figure 5.7)
Prompt to reflect about a specific piece of knowledge	Incorrect answer the learner model shows gap in knowledge (Figure 5.4) or (Figure 5.7)

providing a series of activities that the learner can complete successfully; showing the learner that they have done a good job; and highlighting when a learner has improved a skill.

The robot supports self-reflection and a level of forethought based on the learner giving a correct answer (Figure 5.3), incorrect answer (Figure 5.4), or when the learner inspects a different activity (Figure 5.7). The robot provides support based on the learner's mastery of the current activity and how this interacts with the ideal SRL model.

The learner will only receive these SRL reflection or planning prompts if they are breaking from the ideal model of SRL behaviour developed in section 5.2.

Support for SRL performance phase

Table 5.4 shows the support offered for self-reflection; the reasoning behind which is described in this section. In the discussions with teachers in chapter 3, the teachers identified pedagogical strategies to support the learner, e.g. offering assistance by guiding the learner through instructions; asking questions (to prompt reflection); gestures (to illustrate or focus attention, or indicate shared focus); offering affective support if learners' actions are not optimal (telling them not to worry and try again); and drawing attention back to the task if a learner becomes distracted.

Table 5.4: Robot behaviour to support SRL performance phase

Robot behaviour	Triggers
Positive feedback on tool use	Appropriate tool use (Figure 5.6)
Prompt to use a different tool	Irrelevant tool use (Figure 5.6)
Prompt to not rely upon tool	Learner does not need the tool (Figure 5.6)
Pedagogical support detailed in section 4.6.2	Incorrect answer (Figure 5.4)
Motivational support detailed in Table 4.2	Timeout reached (Figure 5.5)

As above the robot offers the same pedagogical strategies, feedback, and support to engage and perform SRL skills and also to perform well in the task. These pedagogical tactics are described in section 4.6.2. The teachers that were observed in the studies also did a lot to focus the attention of the students to keep them learning in an independent way. Some of the support here overlaps with the support for motivation when the user has not interacted with the activity for a set timeout period (Figure 5.5).

In addition to the high level suggestions for tool use given to the learner in the summary and wrap-up, more detailed and low level support for appropriate tool use is provided when the learner selects a tool (Figure 5.6). When the learner selects a tool the learner model and ideal model of SRL is used to determine if the use of the tool is appropriate or not.

The learner will only receive these prompts if they are breaking from the ideal model of tool use developed in section 5.2.

5.3 Summary of a computational approach to adaptively scaffold SRL

In this chapter the computational approach for scaffolding SRL skills has been presented. The observations from interactions between expert teachers and learners in the learning scenario have been merged with the relevant literature to create a computational model of ideal SRL behaviours in the learning scenario. Deviations from the model are used by a robotic tutor to scaffold SRL support for a learner. In the next section (chapter 6) how effectively the robot can use the ideal model of SRL to scaffold SRL skills will be evaluated.

CHAPTER 6

EVALUATION OF ADAPTIVE ROBOTIC TUTOR

In this chapter the evaluation of the computational model of SRL and the robotic tutor is discussed. The robot's behaviours are intended to scaffold the learner's SRL skills by offering personalised support based on the deviations of the learner from the ideal model of SRL described in section 5.2.

Importantly, to be effective the support for SRL skills must have a social element. A social robotic tutor will be able to support the transition from external regulation, through co-regulation to full self-regulation through demonstration of SRL learning skills as suggest by Roll (Roll et al., 2014b). The design of the learning scenario and the robot's behaviour give more autonomy to the learner as per Roll's suggestions (Roll et al., 2014b). The aim is for the robot and learning scenario to offer close guidance to the learner from low SRL skill level all the way through to the learner being able to fully self-regulate their own learning in this environment. To achieve this the robot will only offer SRL support when the learner is not employing appropriate SRL skills and deviating from the SRL model, as the learner develops these skills they will more closely follow the model and support will then be removed.

While other research has focused on just one aspect of SRL (i.e. help seeking), this approach aims to support a number of SRL phases (self-reflection, forethought, and performance) and to also encourage and motivate the learner. As with adaptive scaffolding in general, interaction with the OLM will be tailored as appropriate to the individual, as will other scaffolding behaviours from the robot. The personalised social scaffolding is based on a learner model of domain knowledge and SRL skills and a model of desired SRL behaviour to deliver support for reflection and planning. This personalised support is delivered by making use of an OLM that displays the learners developing skills. The robot also highlights features in the OLM, thus making the robot part of the OLM as it makes elements of the learner model transparent to the learner. This personalised support encourages the learner to reflect on their knowledge and skills; to make use of good SRL skills to plan to address weaknesses in their knowledge or approach; and to progress to master new material.

The measures that are considered when evaluating the robotic tutor and its impact on the perceptions, learning gain, and SRL skills of the learner are described in section 6.1. A short-term study is described in section 6.2 that investigates how different levels of personalisation of SRL scaffolding impact learners' perceptions of the robot, activity, motivation, SRL skills and learning gain. Finally, a longer-term evaluation is described in section 6.3 where adaptive SRL scaffolding is compared to adaptive domain support.

6.1 Measures

In this section, the measures used to evaluate the learner's interaction with the robot and the learning scenario are considered. Of most concern is how the learner perceives the interaction and the learner's change in academic performance due to the interventions of the robotic tutor. Indeed, it is important to be able to investigate how the learner's perception of the robotic tutor and task may impact on the increase of performance and demonstration of SRL skills in the activity.

6.1.1 Learners' perception of robot and task

How the learner perceives the interaction as a whole is of great interest. It is important that the learners see the robot as a social entity in some form, as this research shows how important social factors are in the development of SRL skills. As discussed in subsection 2.2.4, how the learner perceives the robot will have a large impact on how appropriate the role of the robot is. Also of interest is how the learners perceive the learning task, having spent a lot of time ensuring that the learning scenario as whole is suitable for the development of SRL skills, as set out in section 4.2.

Common approaches and metrics to measure the perceptions of a learner are:

- **Self-report questionnaires**. Self-report questionnaires can offer a wealth of information, including the learners' impressions of the robot's social behaviour (Blancas et al., 2015), the learners' status (Sabourin et al., 2012b), and the learning scenario (Long and Aleven, 2016).

The questionnaire chosen is based on the *Intrinsic Motivation Inventory (IMI)* (McAuley et al., 1989; Ryan, 1982). This is a popular questionnaire that is used to evaluate learners' perceptions of ITS (Sabourin and Lynne, 2013; Long and Aleven, 2016) and also of robotic tutors (Saerbeck and Schut, 2010). The full questionnaire can be found in subsection 8.5.2. This instrument was used to aid understanding of how the differences in the robot's behaviour affected the perception of the robot and the activity. Questions were asked to explore if there were differences in the learner's trust, enjoyment, and engagement with the activity and the robot. Also of interest was whether the learner could perceive the robot's understanding of the learner. The questions are answered on a 7 point scale ranging from 0, "not at all true", to 7, "very true".

The *IMI subject impressions questionnaire* (section 8.5.2) was used, which has sub-scales for *relatedness*, which includes questions related to trust, *interest/enjoyment*, *perceived choice*, and *pressure/tension*. A number of other questions were also put to the learners; *perception of the robot* (section 8.5.2) and *robot help* (section 8.5.2) which overlapped with the IMI subject impressions questionnaire and focused on how the robot helped the learner; *following the robot* (section 8.5.2) which asked about how likely the learner would listen to the robot or do what it says; the *empathy instrument* (section 8.5.2) and *the learner's perception of the robot perceiving the learner* (section 8.5.2) to see if the learner thought the robot perceived or empathised with them (not the learners' empathy towards the robot); and questions concerning the *role of the robot* (section 8.5.2) to see how the learner related to the robot (based on Kennedy's role questions (Kennedy et al., 2015)).

Questions from the *IMI task evaluation questionnaire* (section 8.5.2) were also asked, which has similar scales to the *IMI subject impressions questionnaire* but is more related to the task rather than the robot. The *godspeed* questionnaire which measures key concepts in HRI (Bartneck et al., 2009) was also considered, however, this questionnaire focuses on questions relating to high level perceived anthropomorphism, animacy, likability, intelligence, and safety. An IMI style questionnaire was used as it is more specific in relation to learning and usability.

- **Time spent off task**. This measures how much time the learner spends disengaged from the learning task. It can be used as a proxy for how engaged the learner is in the activity (Ramachandran and Scassellati, 2014). However, this can prove difficult to interpret as the learner may appear disengaged, bored, or frustrated when they are in fact actually thinking (Sabourin et al., 2011).

6.1.2 Robotic tutor's effectiveness

To measure the effectiveness of the adaptive robotic tutor two perspectives are considered: how the learners' performance improves in the learning task; and how the

$$NormalisedLearningGain = \frac{posttest - pretest}{1 - pretest} \tag{6.1}$$

Figure 6.1: Normalised Learning Gain

learners' SRL skills improve in general. It is hoped that the robot's support for SRL will lead to a greater adoption and usage of SRL skills and consequently greater academic performance and an increase in learning gains. In this section the measures used to evaluate the system are discussed, including measures of both learning gain and SRL skills.

Metrics to measure a learner's academic performance

Normalised learning gain This metric is domain specific and normally based on pre and post-test scores. It measures how much the learner has learnt in an interaction (Graesser et al., 2005; Ramachandran and Scassellati, 2014). Learning gains were calculated using Normalised Learning Gain (Hake, 2002), based on the difference between the pre-activity domain test and the post-activity domain test, the calculation is presented in Figure 6.1. In both the pre and post-tests the learners were asked similar questions that cover compass reading, distance measurement, and map symbols. A t-test or one-way ANOVA was used to determine whether there were any statistically significant difference between the Normalised Learning Gain of the groups.

Time per problem This measures the average time for a learner to complete a problem in the learning task correctly (Beck et al., 2000). While this is easy to measure it may not always provide a good indication of learning, as a learner may have mastered a problem and simply be repeating it quickly without learning anything (Ramachandran and Scassellati, 2014).

$$AbsoluteAccuracyIndex = \frac{1}{N}\sum_{i=1}^{N}(c_i - p_i)^2 \tag{6.2}$$

Figure 6.2: Absolute Accuracy Index

Difficulty of problems attempted To solve some of the problems associated with time per problem above, it is possible to calculate the difficulty of questions in an activity by looking at the average success and failure rates (Lin et al., 2015; McCowan et al., 1999), or the average response time. This data can then be used to evaluate the difficulty of a question worked on by the learner.

Metrics for a learner's SRL skills

Self-assessment Self-assessment or perceived competence is an indication of how the learner rates their performance at an activity. A learner's perceived competence may affect how they respond to feedback (Kim et al., 2010; Kollöffel and Jong, 2015); for specific examples see Mr.Collins (Bull and Pain, 1995) or CALMSystem (Kerly et al., 2008). The self-assessment questionnaire is set out in section 8.5.1.

Self-assessment accuracy It is hoped that by using the SRL support offered by the robotic tutor the learners will reflect more on their ability and will be able to make more accurate self-assessments. The Absolute Accuracy Index (Long and Aleven, 2013b; Valdez, 2013; Schraw, 2008) can be used to measure self-assessment accuracy: which represents how closely a learner's self-assessment matches their actual performance. The formula to calculate this is shown in Figure 6.2. "N" is the number of tasks, "c" is the learners' self-assessment, and "p" is the actual performance in the competencies. The closer this figure is to 0 the higher the self-assessment accuracy.

Motivation and SRL self-report As has been discussed in previous sections motivation is a key part of academic performance and SRL. The results of the IMI questionnaires above can be used to judge how motivated a learner is after the interaction. However, it is not possible to use this IMI questionnaire as a before and after test. To carry out a pre and post-test comparison of motivation the *Academic Self-Regulation Questionnaire (SRQ-A)* (Ryan and Connell, 1989) is used, which is reproduced in section 8.5.1. This questionnaire is used to better understand the motivations for a learner to learn. It was developed specifically for late elementary and middle school children (Ryan and Connell, 1989), unlike the *Online Self-regulated Learning Questionnaire* (Barnard et al., 2009) and *Motivated Strategies for Learning Questionnaire* (Pintrich et al., 1993) which are aimed at older age groups. The *SRQ-A* has four sub-scales: *external regulation*, *introjected regulation*, *identified regulation*, and *intrinsic motivation.* The SRQ-A was chosen other self report questionnaires as it was the most appropriate for the age of children.

Measurement of SRL behaviours in the learning task Measurement of a learner's SRL skills or SRL events can be made from the data recorded by a computer based learning scenario (Sabourin and Lynne, 2013). The traces of cognitive, metacognitive and motivational events that are recorded in the learning scenario are essential to the modelling and understanding of a learner's SRL processes (Winne, 2010). The other benefit of using data obtained in this way is that it can be used for stealth assessment, which allows for an assessment of a learner's skills without interrupting the flow of the activity (Shute, 2011). This stealth approach can be applied to SRL learning skills (Sabourin and Lynne, 2013).

Error rate in adherence to ideal model of SRL In section 5.2 a number of the events that indicate the adherence to, or deviation from an ideal model of SRL have been identified. The model is used to measure the error rate or how often a learner deviates from the ideal model of behaviour (Aleven et al., 2006). In this learning scenario a record is kept of the triggers discussed in subsection 5.2.2 and also how often the learner changes activity, their level of mastery at the time that they change activity, and when the OLM is opened and inspected.

Transfer or generalisation of SRL skills It is of interest to see if the skills developed by a learner can transfer to longer-term behaviour change (Tapus et al., 2007) or generalise to other scenarios and contexts (Begum et al., 2016). This research looks at the transfer of skills over time with repeated measurements in a longer-term study as has been done in section 6.3. The near transfer of SRL skills to different tasks is also looked at by changing tasks performed in the activity and seeing if the learner is able to adapt, or if they require additional guidance. The goal is to scaffold a learner's SRL skills so that they can transfer those skills to new learning situations (Roll et al., 2014a).

Other measures Other common measures of SRL behaviour that were not appropriate to the learning activity have also been considered. One set of measures concerns the number of goals and plans set and the rate of achievement against those goals and plans (Lin et al., 2015), however, as there is no way for learners to record goals or plans this cannot be used. Another measure is the number of self-assessments conducted, however, an optional self-assessment tool was not included inside the activity. In the future, as seen in study 4 (section 3.7), it may be useful to have an OLM negotiation mechanism which would provide this type of metric.

6.1.3 Analysis

Using these measures, the research aims to bring together both how the learner perceives the robot and task and how this affects changes in learning performance and SRL skills. The metrics discussed above are used in the studies that follow in this section. A demographic questionnaire (section 8.5.1) is also used so that there is a record of the age and sex of the students for analysis. A number of the measures allow a comparison between the start of the interaction and the end, this can be used to understand how an interaction has affected these metrics, e.g. learning gain can be calculated by looking at the difference between pre and post domain tests, and SRL gain by looking at difference in the *SRQ-A* pre and post-test. Changes over time can also be seen in the interactions from the traces measured inside the learning task.

6.2 Study 5: adaptive SRL study

6.2.1 Introduction

This study is the first evaluation of the fully autonomous robotic tutor and computational model of SRL. A subset of the fully autonomous robot behaviours described in subsection 5.2.2 is used. The interaction is evaluated using the metrics described in section 6.1. Specifically this study explores how personalised tutoring by a robotic tutor, achieved using an OLM, promotes SRL processes and how this can impact learning in primary school children. The robotic tutor provides different levels of personalised SRL scaffolding to primary school children, this is used to investigate the effects of personalisation on SRL feedback. The autonomous robotic tutor's supportive behaviours build upon information provided to a student in an OLM.

6.2.2 Motivation

There is increasing interest and an amount of proposed research exploring how personalisation can make HRI more effective by adapting difficulty levels (Ramachandran and Scassellati, 2014), responding to affective states (Ramachandran and Scassellati, 2015; Jones et al., 2015d), and learning styles (Clabaugh et al., 2015). *Yet, there is no work focusing on how HRI can impact on SRL or meta-cognition in an educational context.* The benefits of a personalised robotic tutor may motivate and engage students to utilise SRL process in the learning scenario.

It is important to encourage or scaffold SRL processes as students may not always be meta-cognitively or motivationally active during the learning process (Azevedo et al., 2011). 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 (Roll et al., 2011). When teachers scaffold SRL with a personalised or adaptive approach it can lead to a learner adopting better SRL skills as compared with conditions where fixed or no scaffolding is offered (Azevedo et al., 2004).

An OLM is adopted as the basis for the personalisation, as this is a simple and intuitive way of displaying to the learners their developing skills; an OLM ensures that the learner has all relevant information upon which to base their reflections and SRL processes. OLM used as a basis for reflective self-assessment activities can increase learning outcomes (Long and Aleven, 2013b; Mitrovic and Martin, 2002).

Research questions

The primary research question is: *do different levels of personalisation of SRL scaffolding impact learners' perception of the robot, activity, motivation, SRL skills and learning gain?* The aim is to identify the effects of personalisation on SRL feedback and how this impacts on child learning. This study investigates the impact of personalised scaffolding on the learner's self-report questionnaires, domain tests, and behaviour in the activity based on activity logs.

Hypothesis

The hypothesis is that more personalised and adapted scaffolding of SRL processes via OLM will lead to higher learning gain and improving SRL processes. This is discussed in detail in section 6.3.2.

6.2.3 Method

In this study a robotic tutor provides different levels of personalised SRL scaffolding to primary school children. To investigate how personalised scaffolding via OLM impacts learning gain and SRL processes, this experiment used four conditions with different levels of robot personalisation. The autonomous robotic tutor's behaviour builds upon information provided to a student in an OLM. This study is a between subject design.

Figure 6.3: NAO robot highlighting OLM to a primary school student

Participants

Schools and teachers were approached and recruited as described in subsection 3.3.1, where the aims of the research project were described to the schools and teachers.

There were 80 (34 female, 46 male) participants of mixed ability levels, all of the students within the year group were able to take part without exclusion or preference for higher ability students. The learners were aged between 10 and 12 and attended the same primary school in the U.K. In accordance with the ethics procedure, informed consent was obtained in writing from the parents and the children participating in the study as outlined in subsection 8.1.2. [redacted]

Procedure

The teachers were emailed the learning activity in advance. Prior to the session with the robot the teachers were asked to allow all of the learners in the class to take part in the activity. The author also gave a presentation at the school about the study. The learners that wanted to participate were given consent forms and information sheets to take home for parents approval.

The study was conducted in a meeting room in the participants' primary school. Each student was brought into the room, given an overview of the study and asked to complete a pre-activity domain test. The autonomous robotic tutor introduced the learning task and then explained how the task and tools work, this is detailed in section 4.6.2. Each student then carried out the activity which was limited to 11 minutes in each session. Each student was then asked to complete a post-activity domain test and a questionnaire with questions about their perception of the robot and the learning scenario. This procedure is shown in Table 6.1.

Experimental setup

The study was conducted in a meeting room in the learner's school. The learners interact with the learning task individually on a touchscreen table. The task runs on a 27 inch touchscreen laid flat on a desk. The learners were standing up to enable

Table 6.1: Procedure details for study 5: adaptive SRL study

Activity	Notes
Overview	Presentation to class to get learners interested in working with the robot
Pre-tests	Domain pre-test (section 8.5.3)
Session	Robot introduces the task. The interaction with the learning task lasts 11 minutes
Debriefing	Domain post-test (section 8.5.3), questions about robot and task (subsection 8.5.2)

them to comfortably reach all areas of the touchscreen. The robotic tutor was an Aldebaran Robotics NAO torso and was fully autonomous during the activity. The robot was positioned on a stand opposite the touchscreen in order for it to be at a similar height to the learner. There were two cameras (one capturing the overall situation and one focusing on the learners' faces). The arrangement of materials is shown in Figure 6.4 and Figure 6.3.

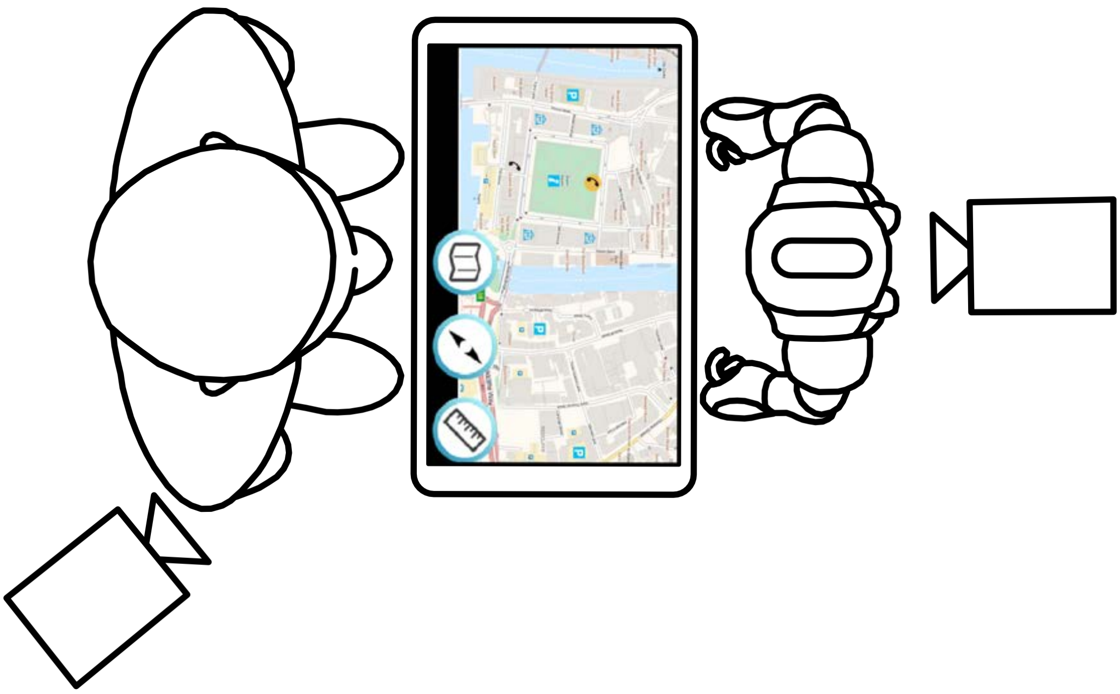

Figure 6.4: Setup for study 5: adaptive SRL study

The task

The autonomous robotic tutor supported individual learners in a geography task, the learning task is described in detail in section 4.2. The task enables the learner to exhibit SRL skills and processes, i.e. self-monitoring, goal setting, and help seeking. The activity was designed to test compass reading, map symbol knowledge, and distance measuring competencies. The learner had a choice of activities of varying difficulty that allowed them to practice the competencies; the menu for this is visible in the lower left of Figure 6.5. The learner was provided with three tools to assist them with the activity. They had 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 lower right of Figure 6.5.

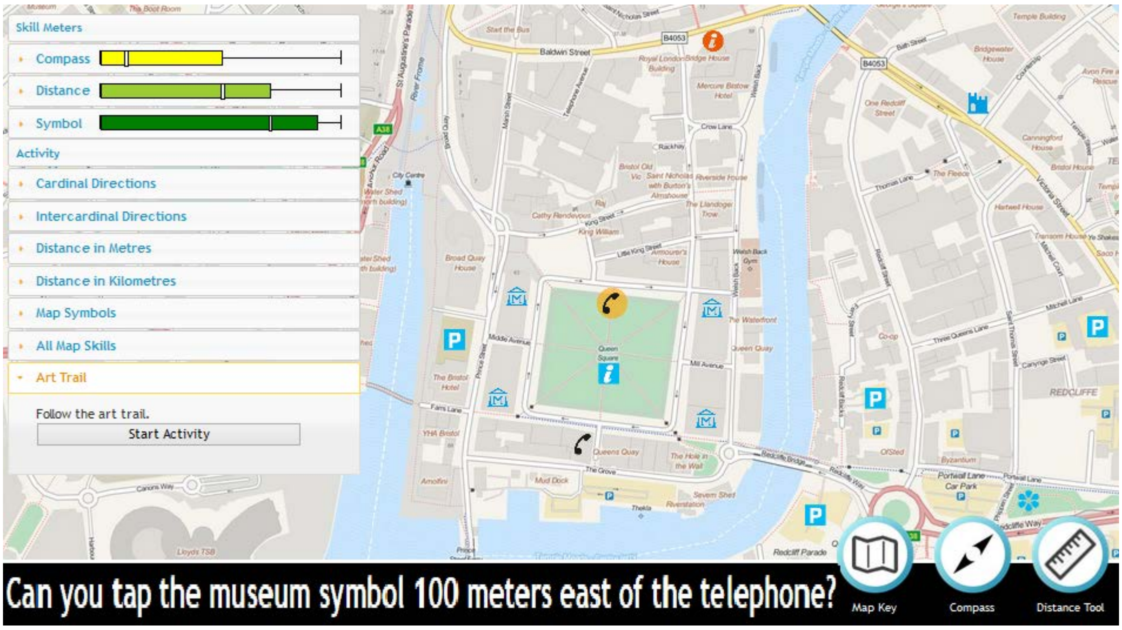

Figure 6.5: Learning task, OLM (upper-left), activity menu (mid-left), instructions (lower-left), tools (lower-right) for study 5: adaptive SRL study

Learner model and OLM

A learner model is built as the basis for the OLM skill meters and 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 (Mitrovic, 2010). Distance and direction are evaluated based on the learner identifying a point on a map that is at 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, a weighted average is used so that recent evidence is given a higher weighting than older evidence in determining the overall level of the competency. Additionally the task gives basic 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. The learner model is described in detail in section 4.3.

An expanded view of the OLM is shown in Figure 6.6. The OLM allows the student to see a visualisation of the learner model that the student can understand their developing skills and identify areas where they have strong or weak knowledge. 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 (Long and Aleven, 2013b). 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. 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 learner 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 helping them identify knowledge gaps, based on this they can then fill their knowledge/skill gaps by selecting an appropriate activity or tool. The OLM is described in detail in section 4.4.

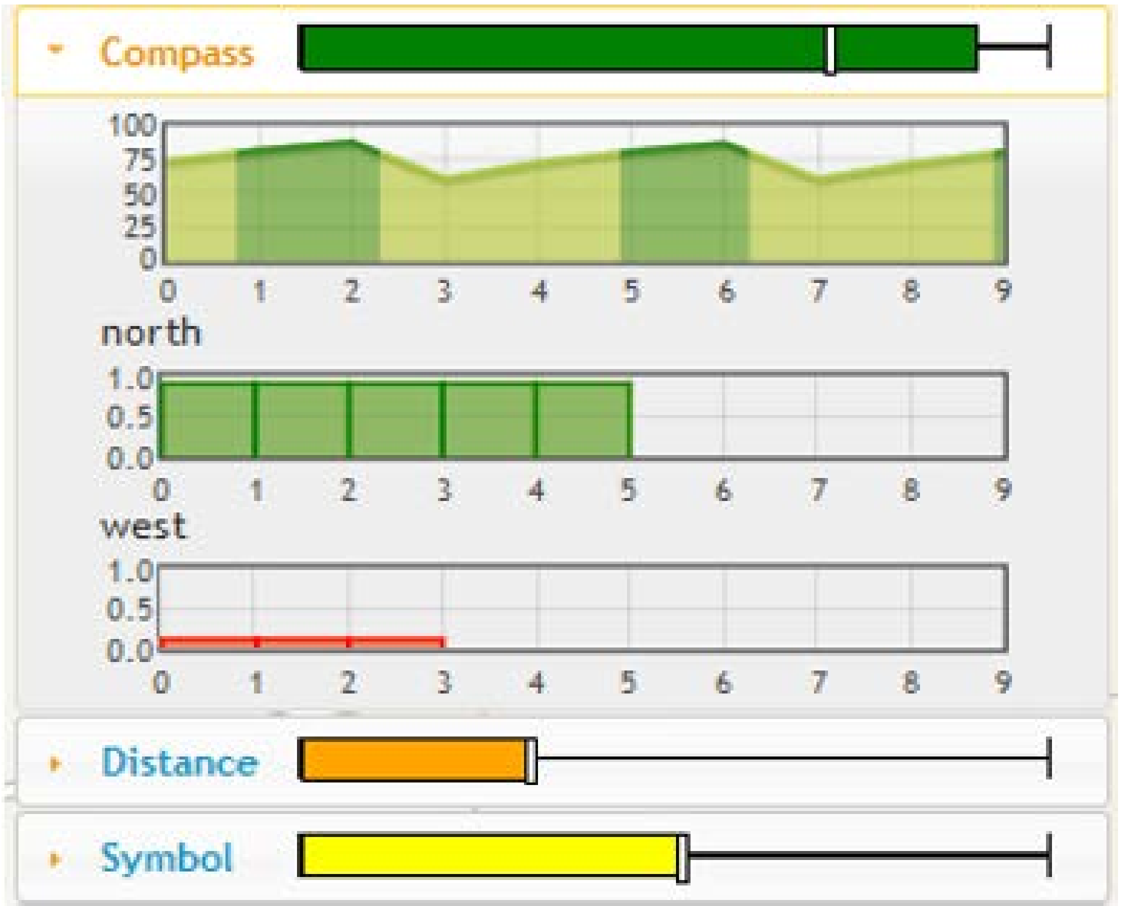

Figure 6.6: Expanded OLM: overall compass competency (high), level of the compass competency over the session (0–100%), 5 correct answer attempts for 'north' (A value of 1 with green), 3 incorrect answer attempts for 'west' (A value of 0 and red), overall distance competency (low), overall symbol competency (medium)

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 weaknesses so that they can effectively plan their learning through selecting appropriate strategies, goals, activities, and using the tools and resources available. The most basic level of scaffolding offered is to provide access to the OLM. To provide more support, static scaffolding can be provided whereby the learner is prompted to use SRL skills at appropriate points in the activity (Azevedo et al., 2004; Koedinger et al., 2009). The highest level of scaffolding would be adaptive scaffolding where support is provided based upon the learner's state (Azevedo et al., 2004; Koedinger et al., 2009).

To support adaptive SRL scaffolding an idealised SRL model has been created for this learning context. Such an approach has been used in another meta-cognitive tutoring system that focuses only on when the student should ask for help (Aleven et al., 2006).

The development of the SRL model is described in chapter 5 and presented in the conference paper Jones, A., Bull, S., and Castellano, G. (2015b). Teacher Scaffolding of Students' Self-regulated Learning using an Open Learner Model. In *Demos and Poster Proceedings (UMAP 2015)* (Jones et al., 2015b). The SRL scaffolding procedures are described in detail in subsection 5.2.2. In earlier UCD studies it was observed that teachers can 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 (Jones et al., 2015b), e.g. teachers would encourage the students to complete the more basic activities until they are proficient before progressing to the more advanced activities.

Based on the previous studies appropriate SRL behaviours in the learning task include:

- Learners should aim to 'master' an activity, this means that they have covered all of the content and are confident in correctly answering the content.
- Learners should move on to a different activity when they 'mastered' an activity.
- Learners should use an appropriate tool to the problem at hand or use the OLM if not confident or incorrectly answering a questions in an activity.
- Learners should stop relying on a tool when they have shown evidence of

being proficient at that type of question, if the learner is using the compass tool when estimated to be proficient at direction questions then this is deemed inappropriate tool use.

The learners' behaviours in the activity are recorded, if a learner is not following the appropriate SRL behaviours outlined above then this is used as a basis for the robotic tutor's behaviours. The robot uses the OLM to prompt the learner to reflect on their developing skills and to use appropriate task strategies and to work at an activity of an appropriate difficulty level. The scaffolding procedures are detailed in Table 6.2. The robot's gestures and speech are based on recordings from the previous study described in section 3.7 (Jones et al., 2015b).

If the SRL scaffolding is effective the students should engage in appropriate SRL processes in the learning task. The indicators of appropriate SRL processes include learning gain; students that are using better SRL processes should learn more in the activity. Due to the way that the robot introduces the activity it is hoped that there are high levels of OLM use, students with higher SRL skills will be aware of the OLM increasing and decreasing, and how getting questions incorrect will effect this. Consequently students should be aware when they answer a question incorrectly and work to address the problem quickly, either identifying their error based on performance, or subsequently use a tool to understand why there is an issue. High levels of SRL are also linked with the number of attempts to obtain a correct answer. In an SRL condition, the learner should realise quickly that they have an issue and correct the problem, so a high level of SRL will have a low average number of attempts at each problem. With high levels of SRL skill there should also be evidence of appropriate tool use. High SRL students will not necessarily have high tool use as they may not need a tool, but any tool use should be appropriately targeted at the problem at hand. A high SRL level student may also take more time over each question, they will work on questions that are at the edge of their ability but will obtain correct answers. Overall, it is important to note that high

SRL students will not necessarily get more questions correct on average or even in total as they should be pushing their zone of proximal development.

Conditions

Four conditions were selected to explore the overall hypothesis. In all cases the robotic tutor is present and gives an introduction to the task and the tools. The robot is fully autonomous. The different robot behaviours and the events that trigger them are summarised by condition in Table 6.2.

There are a number of events that can trigger the robot to execute a behaviour, these are: Answer attempt, when the learner answers a step in the activity; Timeout, when there has been no robot or learner activity in the preceding 15 seconds; and Tool selection, when the learner selects a tool to use. When one of these events occurs the system evaluates if the robot should execute a behaviour according the condition. To avoid repetition or the robot talking too much there are alternative phrases for the robot behaviours and an utterance is not executed if that utterance has been delivered by the robot recently. For example the "Let's keep going we have not covered everything" utterance may be triggered by a timeout, if the learner has not carried out an action for over 15 seconds, or by an answer attempt, but only if the learner has not mastered the activity, meaning they have not shown evidence of correctly answering each aspect of an activity.

SRL_SCAFFOLD. In this condition the autonomous robotic tutor 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. In this condition the autonomous robotic tutor 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 encoded in the pedagogical model described in section 6.3.2 and section 5.2. This is considered an adaptive or dynamic SRL scaffold as it provides feedback on meta-cognitive errors such as using

Table 6.2: Study 5: adaptive SRL study. Robot behaviour and triggers for each condition

Robot Behaviour	Trigger Event	Conditions met
SRL_SCAFFOLD		
Well done, you have mastered this, shall we move on?	Timeout or Answer	Correct answer & Activity is mastered
Let's keep going we have not covered everything	Timeout or Answer	Correct answer & Activity not mastered
Let's keep going we need to focus on south	Timeout or Answer	Incorrect answer & Activity not mastered
We need to focus on south; is there a tool that can help?	Timeout or Answer	Incorrect answer & Activity not mastered
We need to focus on south; should we do an easier task?	Timeout or Answer	Incorrect answer & Activity not mastered
This tool should help!	Tool selected	Appropriate tool selected
Is there another tool that can help you?	Tool selected	Inappropriate tool selected
You know this! Do you still need the tool?	Tool selected	Inappropriate tool selected
Positive beeping and gestures	Answer	Correct answer
Sympathetic beeping and gestures	Answer	Incorrect answer
SRL_PROMPT		
Do you think you have mastered this activity?	Timeout	
Is there a tool that can help you?	Timeout	
Should we do an easier activity?	Timeout	
Let's look at the evidence to see what you should focus on?	Timeout	
Positive beeping and gestures	Answer	Correct answer
Sympathetic beeping and gestures	Answer	Incorrect answer
OLM_ONLY		
Idle behaviours	Continuous	
CONTROL		
Idle behaviours	Continuous	

an inappropriate tool or continuing with an activity that is too easy or too challenging (Koedinger et al., 2009).

SRL_PROMPT. In this condition the autonomous robotic tutor offers static reflective SRL prompts that are triggered by certain actions of the learner. The SRL scaffolding is considered static as it is not dependent on the state of the student's meta-cognition as it is in the above condition (Koedinger et al., 2009). The feedback is still personalised as feedback is contingent on the learner's actions.

OLM_ONLY. This control condition contains limited personalised feedback in the form of an OLM. After introducing the activity and tools the robot simply performs idle behaviours. This condition allows the investigation of the impact of the adaptive and static SRL scaffolding over the OLM 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 simply performs idle behaviours.

In all conditions the robot introduces the learning task, tools, and performs idle motions throughout the session. The robot only uses pointing in the *SRL_SCAFFOLD* and *SRL_PROMPT* conditions and only towards the OLM and not at any other time. Therefore, it is not believed that this will prompt greater engagement or focus in the activity.

Hypothesis

The specific hypotheses are as follows:

Hypothesis 1 (H1). Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than static SRL scaffolding.

Hypothesis 2 (H2). Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than an OLM alone.

Hypothesis 3 (H3). Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding.

Hypothesis 4 (H4). Static SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than access to an OLM alone.

Hypothesis 5 (H5). Static SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding.

Hypothesis 6 (H6). Access to an OLM alone will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding.

A number of questions are asked in the post-activity questionnaire based on the Intrinsic Motivation Inventory (IMI) (McAuley et al., 1989; Ryan, 1982). It is hypothesised that differences in the robot's behaviour will impact the perception of the robot and the task.

Hypothesis 7 (H7). The perception of the robotic tutor will differ between conditions. The robot's behaviour will affect the learner's perception of the robot, the role of the robot, and the learner's attitude towards the robot.

Hypothesis 8 (H8). The perception of the activity will differ between conditions. The robot's behaviour will affect the learner's perception of their competence in the activity, the importance/value/interest in the activity, and the perception of the OLM skill meters.

It is expected that the differences in conditions will effect the less able students to a greater degree than the more able students who may already have strong domain knowledge and good SRL skills, which would be similar to findings in related OLM research (Mitrovic, 2007).

There are no specific hypothesis regarding the questionnaire data. It is expected that the robot will add enjoyment and motivation to the activity as it is a novel and exciting prospect for the students and this may overcome any other concerns that the learner may have about the learning scenario.

Data collection

Audio and video recordings were made by the author. Two cameras were used, one capturing the overall situation and one focusing on the participants' faces. The task recorded all interactions with the touchscreen to a log file and database. A domain pre-test questionnaire was given the learners before the session, this is detailed in section 8.5.3. A domain post-test, detailed in section 8.5.3, and a questionnaire about the learner's experience with the robot and task was given to the learners after the learning session. The questions asked in the post-activity questionnaire are based on the IMI (McAuley et al., 1989; Ryan, 1982). This is described in detail in subsection 6.1.1 and subsection 8.5.2. These questions aim to investigate how the differences in the robot's behaviour affected the perception of the robot and the activity. Specifically, if there were differences in the learner's enjoyment, engagement with the activity and the robot. Additionally they seek to investigate if the learner could perceive the robot's understanding of the learner. The questionnaire was in the form of a series of Likert style questions.

6.2.4 Results

Data Analysis

The results presented here are derived from the analysis of the log data and domain pre-activity and post-activity tests and questionnaires. Counts of events from log data was extracted by querying the database and processing of the log file. The event counts, domain test results, and questionnaire responses were then entered into SPSS for the analysis described below.

The analysis is broken down to investigate differences between more able and less able students based on whether the learner was above or below the mean of the pre-test domain score as has been the measure in related OLM research (Mitrovic and Martin, 2002; Mitrovic, 2007); the breakdown is presented in Table 6.3.

The video recordings were reviewed to understand if the learners experienced any usability issues, but have not formed the basis of any further evaluation.

Table 6.3: Participant details for Study 5

Condition	Total	Less able	More able
SRL_SCAFFOLD	24	12	12
SRL_PROMPT	20	7	13
OLM_ONLY	15	9	6
CONTROL	21	11	10

Significant differences (lower than 0.05) between conditions are highlighted with a connecting black line in the figures below.

Learning gain

Learning gains were calculated using Normalised Learning Gain (Hake, 2002), based on the difference between the pre-activity domain test and the post-activity domain test, the calculation is presented in Figure 6.1 and described in section 6.1.2. In both the pre and post test the learners were asked 14 questions that cover compass reading, distance measurement, and map symbols. A one-way ANOVA was used to determine whether there was any statistically significant difference between the Normalised Learning Gain of the groups.

If SRL processes are used the learners should have spent time focusing their learning on activities that are not within their knowledge. After the session this should lead to an increased score on the post-test.

The results in Figure 6.7 show that there was a statistically significant difference between groups as determined by one-way ANOVA ($F(3,70) = 3.916$, $p = .012$) when considering all students. A Tukey post hoc test revealed that the learning gain in the *SRL_SCAFFOLD* condition (M=0.58, SD=0.3) is significantly higher than *OLM_ONLY* condition (M=0.20, SD= 0.3, $p = .009$) when considering all students. There were no other statistically significant difference between the groups. There is a general trend when considering all students, more able students, and

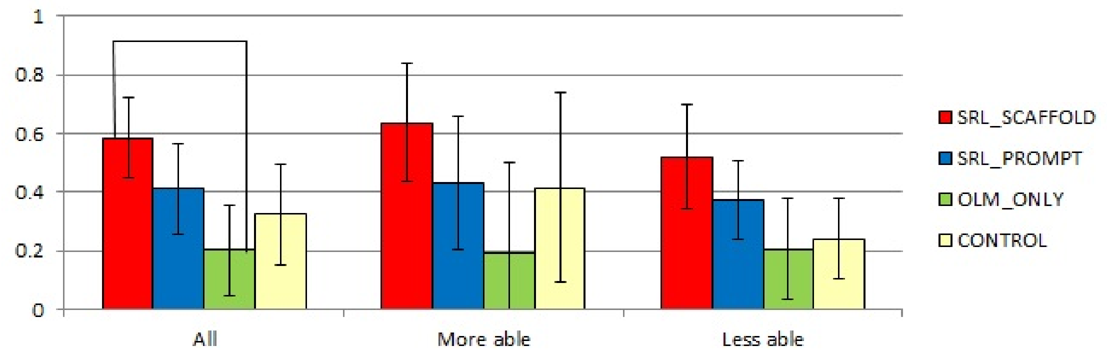

Figure 6.7: Normalised Learning gain: all learners (left), more able (centre) and less able students (right)

less able students that learning gain is highest for *SRL_SCAFFOLD* followed by *SRL_PROMPT* then *CONTROL* and finally *OLM_ONLY*.

SRL indicators in task performance data

The indicators that have been extracted from the logs aim to measure SRL behaviours. One-way ANOVAs were used to determine whether there was any statistically significant difference between the indicators of the groups.

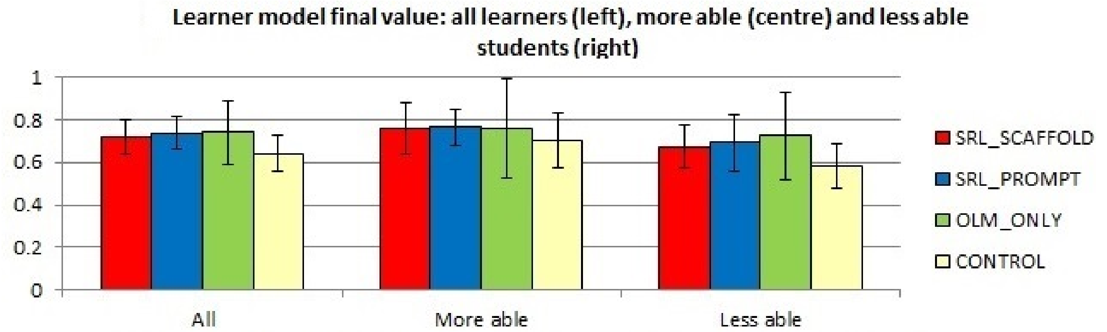

Figure 6.8: Learner model final value: all learners (left), more able (centre) and less able students (right)

Learner model final value. This is the average of all the skill levels from the learner model at the end of the activity. It is an indicator of how well the student is at the content in the activity that they have attempted to answer. If the learners are using the OLM to reflect and SRL processes are used, then the students should be looking to ensure that their actions lead to an increase in the OLM skill meters.

To do this the students should be working on getting answers correct by using the tools rather than guessing and getting lower learner model values. This value is based on the evidence provided, it shows performance on the questions attempted by the learner. It does not consider coverage of the content of the activity. It is possible to have a high learner model value by answering simple questions so it is not an indicator of total level of knowledge or ability.

The results in Figure 6.8 show that in the *CONTROL* condition the learner model value is generally lower than all other conditions. However, there are no statistically different results.

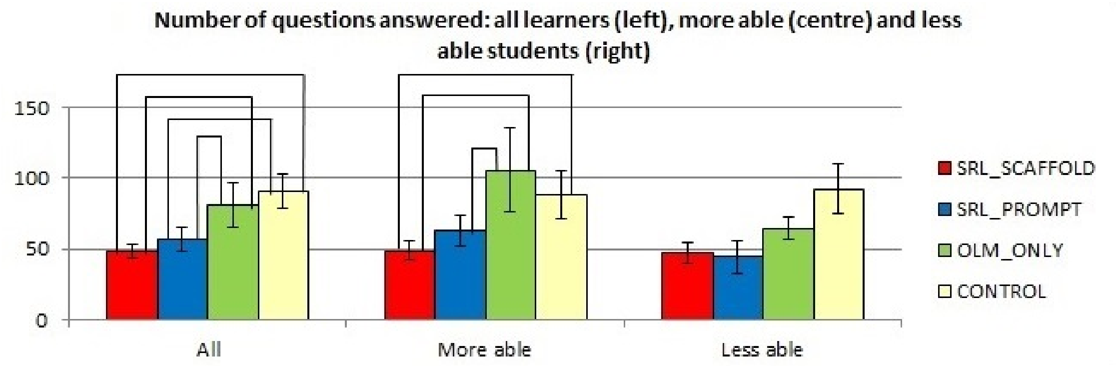

Figure 6.9: Number of questions answered: all learners (left), more able (centre) and less able students (right)

Number of questions answered. This gives an indication of how long a learner spends on each question; A learner could complete fewer questions because that learner is struggling, distracted, reflecting more, or making use of tools. This indicator must be taken into account with the indicators that follow in this section.

The results inFigure 6.9 show a statistically significant difference between groups as determined by one-way ANOVA when considering all students ($F(3,76) = 15.72$, $p = .000$) and more able students ($F(3,35) = 12.888$, $p = .000$). A Tukey post hoc test revealed the following statistically significant differences. When considering all students the learning gain *SRL_SCAFFOLD* (M=48.16, SD= 12.1) learners complete significantly fewer questions than *OLM_ONLY* (M=81.00, SD= 31.9, p =.000) and *CONTROL* (M=90.61, SD= 27.8, p =.000) conditions, the *SRL_PROMPT*

(M=56.70, SD= 20.0) learners complete significantly fewer questions than *OLM_ONLY* (M=81.00, SD= 31.9, p =.015) and *CONTROL* (M=90.61, SD= 27.8, p =.000) learners. When considering more able students *SRL_SCAFFOLD* (M=48.19, SD= 11.8) learners complete significantly fewer questions than *OLM_ONLY* (M=105.83, SD= 37.1, p =.000) and *CONTROL* (M=88.60, SD= 26.8, p =.001), *SRL_PROMPT* (M=63.15, SD= 19.7) learners complete significantly fewer questions than *OLM_ONLY* (M=105.83, SD= 37.1, p =.003).

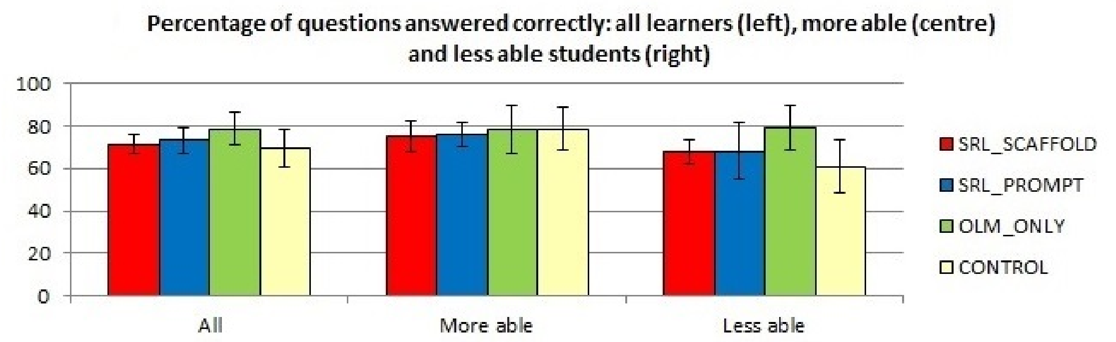

Figure 6.10: Percentage of questions answered correctly: all learners (left), more able (centre) and less able students (right)

Percentage of questions answered correctly. This gives an indication of how deliberately the students are answering questions. If this is high then it shows that the student is getting most question attempts correct, however this may not always be desirable because it can indicate that the student is focusing on questions that they may already know the answer to and are not pushing themselves.
The results in Figure 6.10 show there are no statistically different results.

Attempts until a successful answer. This 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.

The results in Figure 6.11 do not show statistically significantly different values between conditions, however in the *CONTROL* condition learners take more attempts to get a correct answer, particularly the less able learners. This may indi-

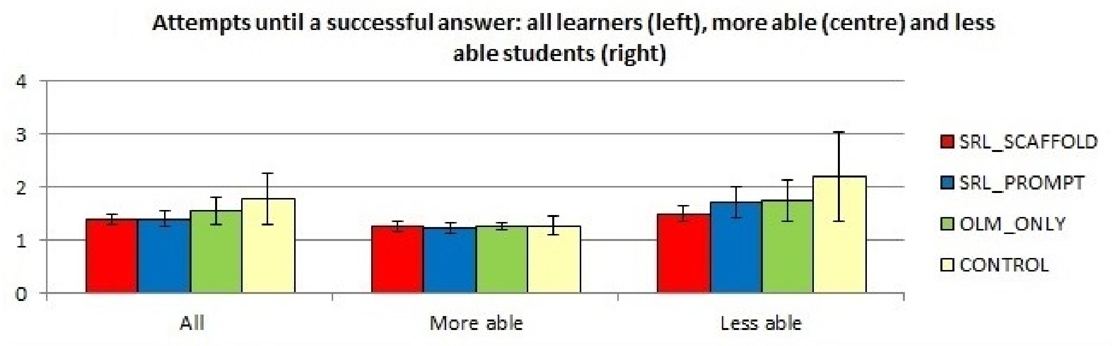

Figure 6.11: Attempts to obtain a successful answer: all learners (left), more able (centre) and less able students (right)

cate that learners in the control condition are not taking appropriate SRL actions when they are getting questions incorrect.

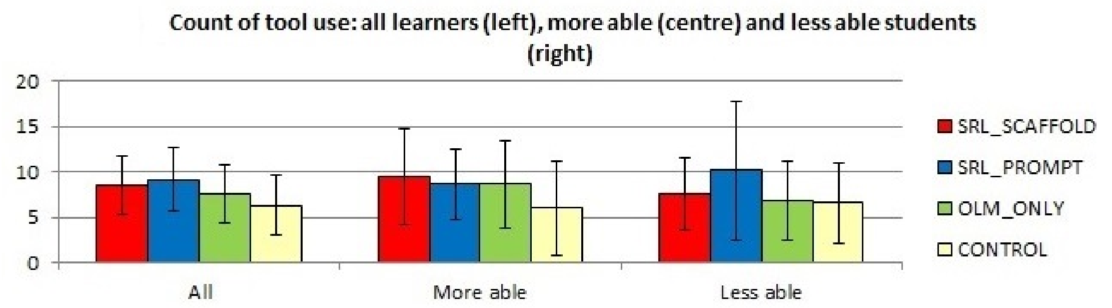

Figure 6.12: Count of tool use: all learners (left), more able (centre) and less able students (right)

Tool use. This is a count of tool use in the activity.

The results in Figure 6.12 do not show statistically significant differences between conditions, however in the *CONTROL* condition the tool use is lower than the other conditions. This may indicate that the students do not realise that they have issues or that the tools can help them with address the issues.

When the indicators are taken together some general trends can be observed between the conditions. In the adaptive scaffolding condition *SRL_SCAFFOLD* indicates a greater adoption of SRL behaviours. More time is taken over fewer questions, the number of steps to get a correct answer are fewer; however, the percentage of correct answers is lower, which may indicate that the learner is working on more challenging questions. This may be a factor in the higher learning gains for this group.

In the static scaffolding condition *SRL_PROMPT* the adoption of SRL behaviours seems similar to *SRL_SCAFFOLD*, however this does not translate to as high a degree of learning gain.

The *OLM_ONLY* condition indicates a lesser degree of SRL behaviours, less time is taken over more questions, and a slightly higher percentage of questions are answered correctly, which indicates that the students are spending more time on questions that they find comfortable. So the learners perform well but do not appear to push themselves.

The control condition *CONTROL* appears to have the least degree of SRL behaviours; learners take the least time over the greatest number of questions, they have a lower percentage of questions correct, and take more attempts to get a successful answer, and the tool use is low. The learner model final values are also lower. This indicates that the learners are not aware of where they have issues and do not work to address these issues with the tools available.

Questionnaire results

There was not a specific hypothesis concerning the learner and how they might perceive the robot. Each question was asked on a 7 point scale ranging from 1, "not at all true" to 7, "very true". The mean values of each sub-scale of the IMI and the individual items were analysed by comparing each condition against each other using a Mann-Whitney U test. The significant values (lower than 0.05) were then further investigated. The reliability of these sub-scales is reported using Cronbach's alpha.

Learner's perception of the robot. This sub-scale consists of questions about the learner's perception of the robot. The Cronbach's Alpha for this grouping was .864. In Figure 6.13 the value for the perception was significantly higher in the

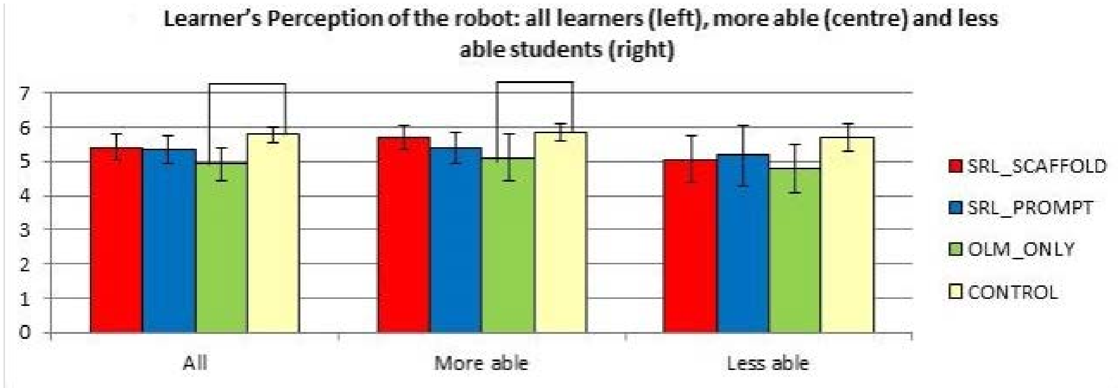

Figure 6.13: Learner's perception of the robot: all learners (left), more able (centre) and less able students (right)

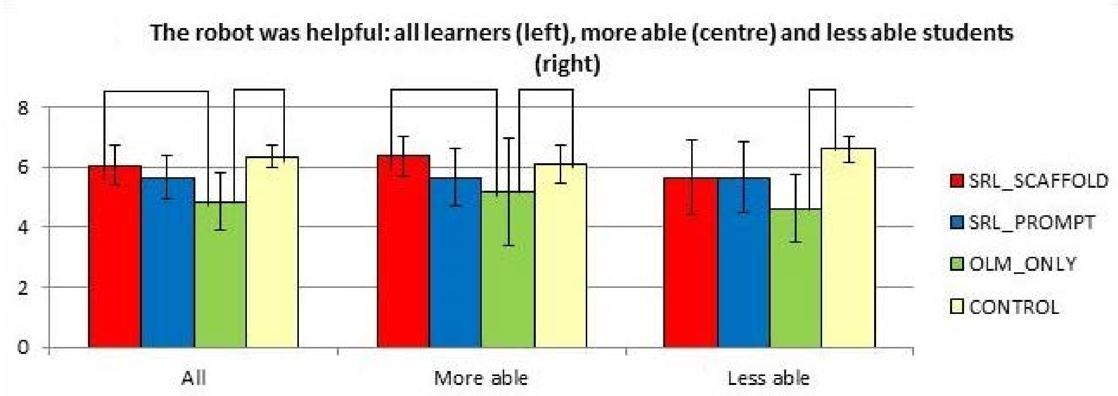

Figure 6.14: The robot was helpful: all learners (left), more able (centre) and less able students (right)

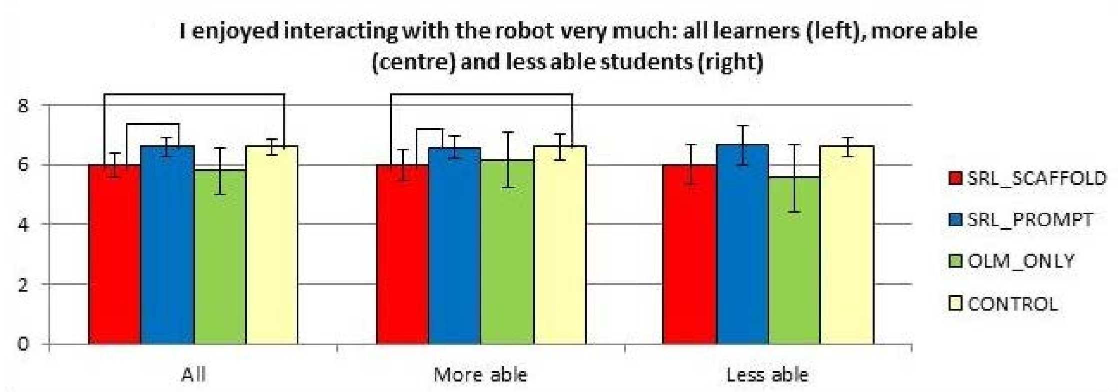

Figure 6.15: I enjoyed interacting with the robot very much: all learners (left), more able (centre) and less able students (right)

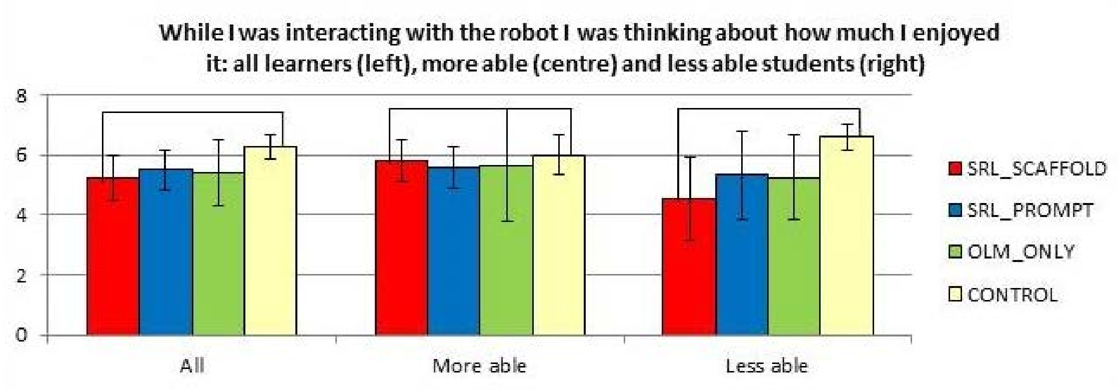

Figure 6.16: While I was interacting with the robot I was thinking about how much I enjoyed it: all learners (left), more able (centre) and less able students (right)

CONTROL condition than the *OLM_ONLY* condition (U = 66.000; p= .010).

The question that contributes the most to this is the question "the robot was helpful". In Figure 6.14 the robot was rated significantly less helpful in the *OLM_ONLY* than the *CONTROL* (U = 72.500; p= .013) and the *SRL_PROMPT* (U = 85.000; p= .041).

It also appears that the learners did not enjoy the *SRL_SCAFFOLD* condition as much as the *CONTROL* condition. In Figure 6.15 for the question "I enjoyed interacting with the robot very much" the *SRL_SCAFFOLD* is significantly lower than the *SRL_PROMPT* (U = 110.000; p= .025) and *CONTROL* (U = 125.000; p= .027).

In Figure 6.16 that for the question "While I was interacting with the robot I was thinking about how much I enjoyed it" the *SRL_PROMPT* condition is lower than the *CONTROL* condition (U = 130.500; p= .047).

Learner's perception of the robot's perception of the learner. This subscale consists of questions about how the learner felt the robot perceived them. The Cronbach's Alpha for these questions was .575, which is a rather low value. In Figure 6.17 that the *OLM_ONLY* condition is significantly less than the *SRL_SCAFFOLD* condition (U = 77.500; p= .028) and *CONTROL* (U = 53.000; p= .002).

The *OLM_ONLY* condition is consistently and significantly lower across the

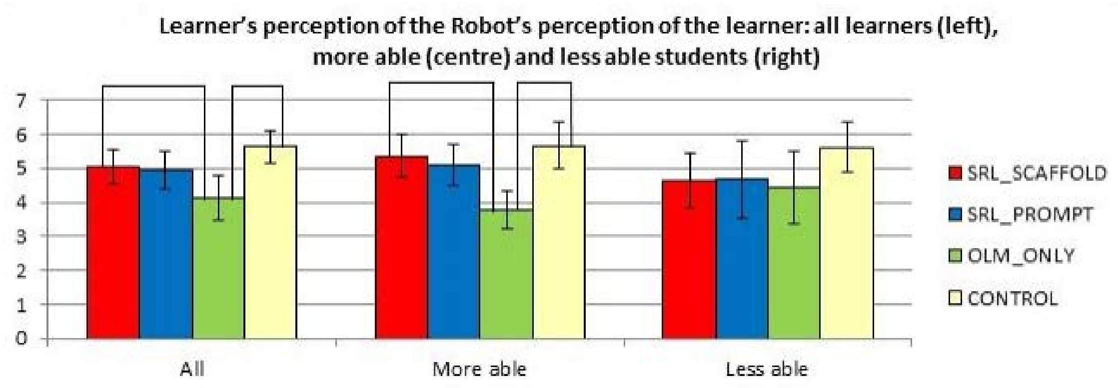

Figure 6.17: Learner's perception of the robot's perception of the learner: all learners (left), more able (centre) and less able students (right)

questions than all of the other conditions. These questions were "I feel that the robot understands me", "The robot was happy for me when I was doing well", "The robot felt sorry for me when I was having problems". This indicates that the learners were aware that the robot was not helping them when their issues were highlighted by the OLM.

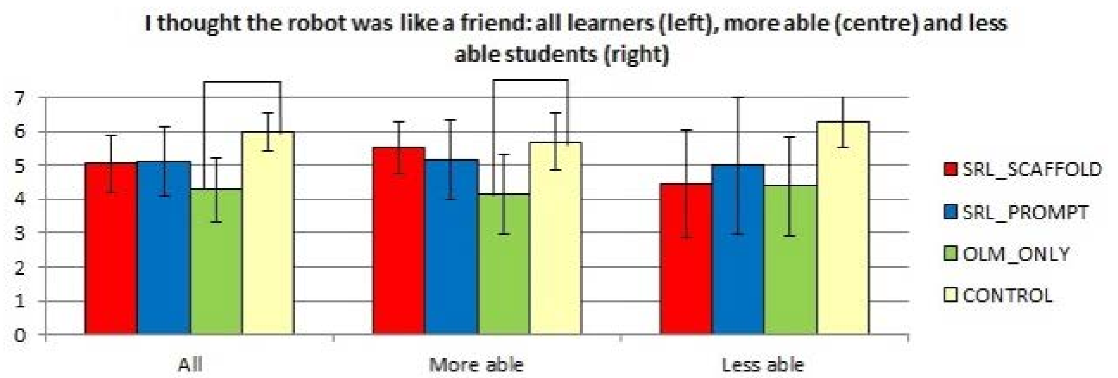

Figure 6.18: I thought the robot was like a friend: all learners (left), more able (centre) and less able students (right)

Role of the robot. This sub-scale consists of questions about the learners' perception of the role of the robot. The learner was asked to mark on a scale from 1 to 7 how much the robot was like a classmate, friend, or teacher. The details are in section 8.5.2. In Figure 6.18 the only significant difference between conditions was for the question "I thought the robot was like a friend"; the *CONTROL* condition is given a significantly higher value than the *OLM_ONLY* condition (U= 63.000,

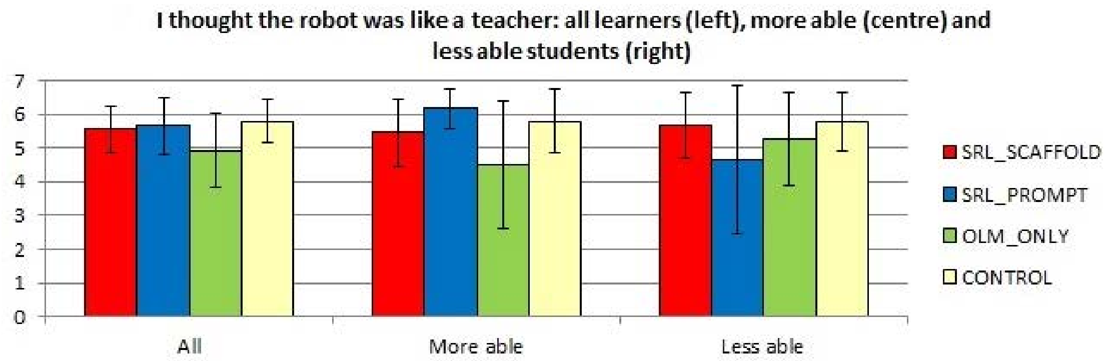

Figure 6.19: I thought the robot was like a teacher: all learners (left), more able (centre) and less able students (right)

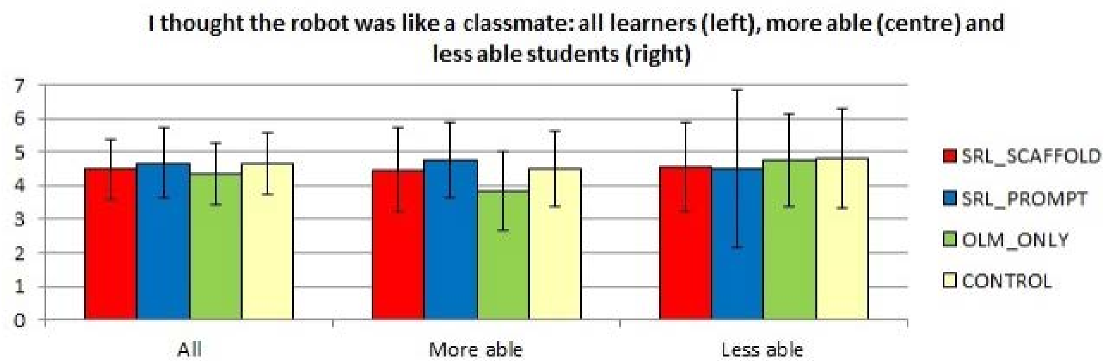

Figure 6.20: I thought the robot was like a classmate: all learners (left), more able (centre) and less able students (right)

p=.005). There are no significant differences between the conditions for how the robot is perceived as a teacher Figure 6.19 or as a classmate Figure 6.20.

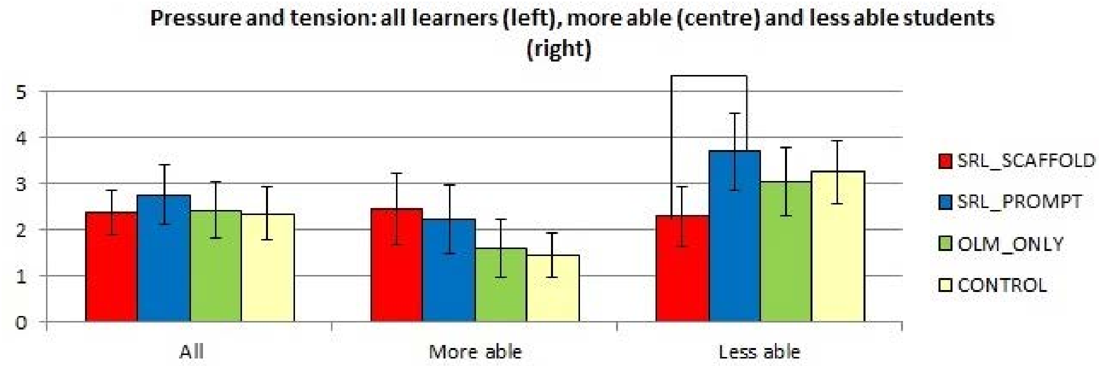

Figure 6.21: Pressure and tension: all learners (left), more able (centre) and less able students (right)

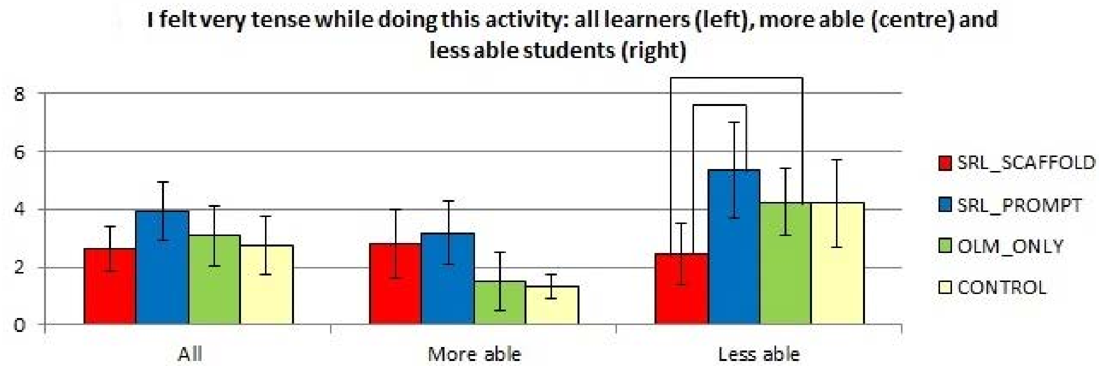

Figure 6.22: I felt very tense while doing this activity: all learners (left), more able (centre) and less able students (right)

Pressure and tension. This sub-scale measures the pressure and tension the learner perceives in the activity. The Cronbach's Alpha for the questions that compose the *pressure/tension* sub-scale from the IMI task evaluation questionnaire was .629. Figure 6.21 shows that the pressure sub-scale is significantly higher in the *SRL_PROMPT* condition than the *SRL_SCAFFOLD* condition for less able students (U = 9; p= .033).

Figure 6.22the *SRL_SCAFFOLD* for the question "I felt very tense while doing this activity" for less able students is significantly lower than the *SRL_PROMPT* condition (U = 7; p= .016) and the *OLM_ONLY* condition (U = 15.5; p= .044).

This indicates that In the *SRL_SCAFFOLD* and *OLM_ONLY* conditions the learner is made more aware of issues but has less support from the robotic tutor. The less able students are less able to identify how to solve the problems or may not be as used to engaging in SRL processes that are now required which could explain the increased pressure that they feel. The *SRL_SCAFFOLD* condition gives the learner specific personalised strategy that can reduce the pressure that the learner feels.

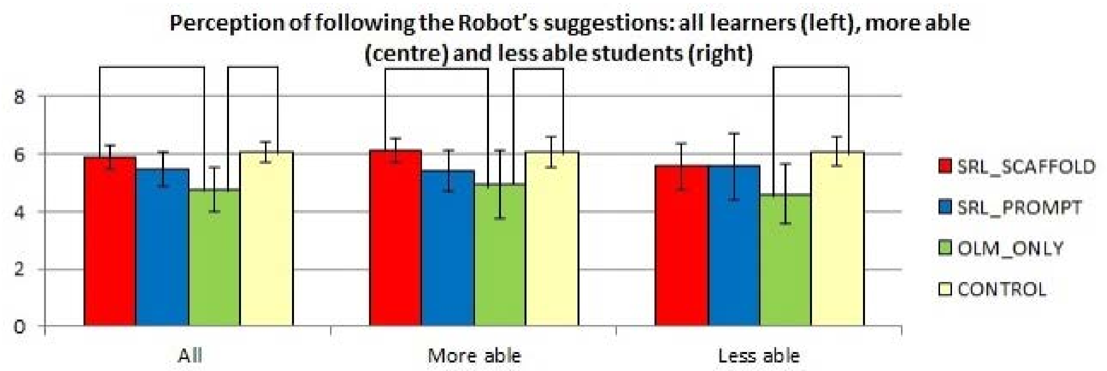

Figure 6.23: Perception of following the robot's suggestions: all learners (left), more able (centre) and less able students (right)

Following the robot. This sub-scale consists of questions about whether the learner followed advice from the robot. The Cronbach's Alpha for this grouping was .861. In Figure 6.23 the value for *OLM_ONLY* is significantly lower than the *SRL_SCAFFOLD* (U = 78.000; p= .030) and *CONTROL* (U = 59.500; p= .005) conditions.

The *OLM_ONLY* is consistently and significantly lower across the questions than all of the other conditions. These questions were "The robot helped me decide what to do next", "The robot helped me choose the right tools".

Interest in the activity. This sub-scale measures how much interest or enjoyment the learner perceives in the activity. The Cronbach's Alpha for the questions that compose the *interest/enjoyment* sub-scale from the IMI task evaluation questionnaire was .793. In Figure 6.24 the interest and enjoyment is fairly similar between all conditions. There is higher interest/enjoyment with the *CONTROL*

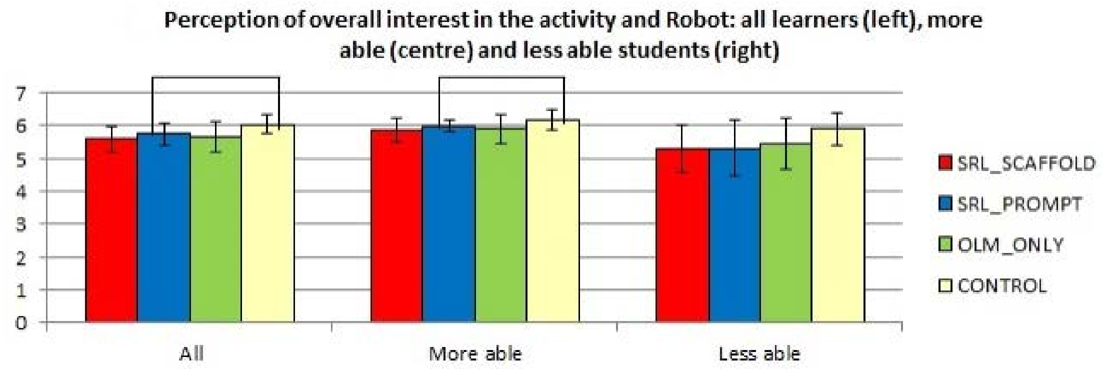

Figure 6.24: Perception of overall interest in the activity and robot: all learners (left), more able (centre) and less able students (right)

condition overall (U = 105; p= .047). This might be linked with how the learners in the control condition perceived the role of the robot.

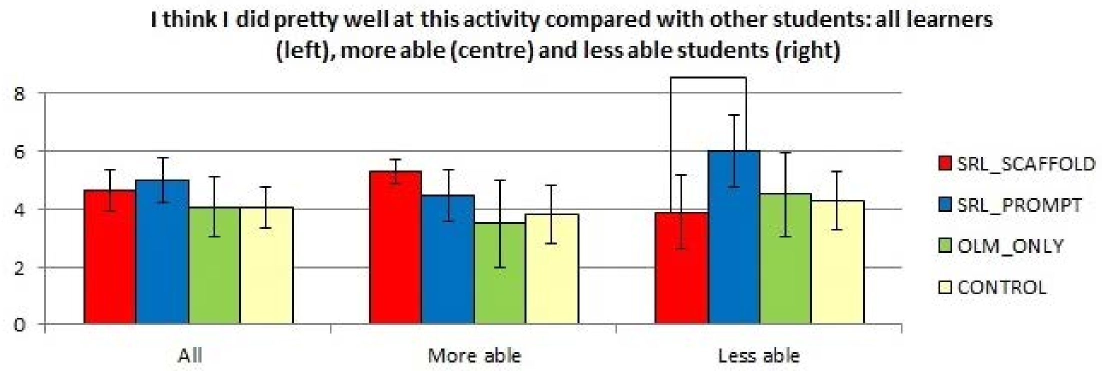

Figure 6.25: I think I did pretty well at this activity compared with other students: all learners (left), more able (centre) and less able students (right)

Perceived competence. This sub-scale measures the how competent the learner thinks they are at the activity. The Cronbach's Alpha for the questions that compose the *perceived competence* sub-scale from the IMI task evaluation questionnaire was .700. There are no significant differences between the conditions in the sub-scale.

It is observed that in Figure 6.25 that one interesting result is that for the question "I think I did pretty well at this activity compared with other students" for less able students the *SRL_SCAFFOLD* is significantly lower than the *SRL_PROMPT* (U=9.000, p=.031). This indicates that the less able students must notice an improvement in their skills when pushed by feedback from the robot in a more “hard won” context.

Importance and value of activity. There are two sub-scales from the IMI activity evaluation questionnaire that measure the how important and valuable the task was to the learner. The Cronbach’s Alpha for the questions that compose the *importance* sub-scale was .700 and the *value* sub-scale was .817. There are no significant differences between the conditions in the sub-scale. This indicates that there is no difference in levels of motivation to complete the task.

Skill meters. This sub-scale measures the learners’ perception of how the skill meters helped them. The Cronbach’s Alpha for this grouping was .859. There are no significant differences between the conditions.

6.2.5 Discussion

Summary of findings

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

A higher level of personalisation and adaptive scaffolding of SRL seems to lead to greater adoption of SRL behaviours and an increase in learning gain. Less able students in the SRL conditions appear to have been helped the most. All students should be familiar with the material as it is part of the National Curriculum, on average the pre-test domain scores were 6.4 out of 10 (SD.1.83) and post-test domain scores were 7.6 out of 10 (SD. 1.79).

Without any SRL support in the control condition, learners do not appear to engage many SRL processes. The presence of a robot may motivate the students to engage in the learning scenario, in fact the robot in the control condition is the most well perceived in terms of enjoyment, motivation, and being thought of as a friend.

However this does not necessarily foster SRL processes, appropriate scaffolding must still be made available.

An OLM on its own does not lead to students engaging in SRL processes. Making the learner aware of their issues via an OLM but not providing specific help can increase the pressure experience by the learner, it was observed that higher levels of pressure were reported in the *SRL_PROMPT* and *OLM_ONLY* conditions. Some pressure and tension is good for learning as it will prompt the learner to take some action, however too much pressure could cause the learners to become disengaged. If the robot is present with an OLM it should offer some support to assist the learner. Otherwise the learner will perceive the robot poorly and may not follow its advice in the future.

In general the adaptive scaffolding condition (*SRL_SCAFFOLD*) indicates a greater adoption of SRL behaviours. More time is taken over fewer questions, and the number of steps to get a correct answer are fewer. However, although the percentage of correct answers is lower, this may indicate that the learner is working on more challenging questions. This appears to translate into higher learning gains.

In the static scaffolding condition (*SRL_PROMPT*) the adoption of SRL behaviours seems similar, however this does not translate to as high a degree of learning gain.

The OLM only condition (*OLM_ONLY*) indicates a lesser degree of SRL behaviours; less time is taken over more questions, a slightly higher percentage of correct questions was observed which indicates that the students are spending more time on questions with which they are more comfortable. So the learners perform well but appear to not be challenging themselves.

The control condition (*CONTROL*) appears to have the least degree of SRL behaviours; learners take the least time over the greatest number of questions, they have a lower percentage of questions correct, take more attempts to get a successful answer, and the tool use is low. The learner model final values are also lower, which indicates that the learners are not aware of where they have issues and do not work to address these issues with the tools available.

Review of hypothesis

H1, *Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than static SRL scaffolding*, is not supported, as there are not statistically significant higher learning gains between students in the personalised conditions for adaptive scaffolding *SRL_SCAFFOLD* and static scaffolding *SRL_PROMPT*. In terms of SRL indicators there does not appear be a difference.

H2, *Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than an OLM alone*, is supported, as personalised adaptive SRL scaffolding *SRL_SCAFFOLD* as compared with a personalised *OLM_ONLY* alone leads to significantly higher learning gains and more time spent on fewer questions. The key difference appears to be that the OLM alone does not prompt the learner to push on to more difficult questions as can be seen with the higher percentage of questions correct.

H3, *Adaptive SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding*, is supported, as personalised adaptive SRL scaffolding *SRL_SCAFFOLD* as compared with a the *CONTROL* condition leads to significantly higher learning gains and more time spent on fewer questions. The learners in the control conditions show the least indication of SRL behaviours; they do not appear to be aware of or able to act on their weaknesses in the activity.

H4, *Static SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than access to an OLM alone*, is supported, as personalised static SRL scaffolding *SRL_PROMPT* as compared with an OLM alone *OLM_ONLY* leads to significantly higher learning gains when considering all students. As with H2 the key difference appears to be that the OLM alone does not prompt the learner to push on to more difficult questions as can be seen with the higher percentage of questions correct.

H5, *Static SRL scaffolding will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding*, is not supported, as there is no statistically significant difference in learning gain in the personalised static SRL scaffolding *SRL_PROMPT* as compared with the *CONTROL* condition.

H6, *Access to an OLM alone will lead to a greater increase in learning gain and more appropriate SRL learning behaviour than no scaffolding*, is not supported, as learning gain does not differ significantly between the OLM only *OLM_ONLY* and the *CONTROL* condition. In fact there appears that there might even be more learning gain in the *CONTROL* condition.

With regard to the questions to ascertain the learner's perception of the learning activity and the role of the robot.

H7, *The perception of the robotic tutor will differ between conditions.* The robot's behaviour will affect the learner's perception of the robot, the role of the robot, and the learner's attitude towards the robot, is supported, as the different conditions appear to have affected the way that learners perceive the robot and if they would listen to the robot in the future. In the *OLM_ONLY* condition the robot is perceived the least favourably. In the *CONTROL* condition the robot was perceived surprisingly positively, the robot did exactly the same behaviour as the *OLM_ONLY* condition but as the students were not as aware of their difficulties the robot is perceived as a friend.

H8, *The perception of the activity will differ between conditions.* The robot's behaviour will affect the learner's perception of their competence in the activity, the importance/value/interest in the activity, and the perception of the OLM skill meters, is supported, as the different conditions appear to have affected the way that learners perceive the task. The students in the *SRL_PROMPT* condition felt most like they have performed better in the task than other students. This could be because they were aware of overcoming problems themselves without much assistance. These students also felt some stress due to the lack of assistance when they were aware of their weaknesses. The students in the *OLM_ONLY* condition were aware that the robot was not helping them and consequently had a low perception of the robot. These students also felt tense. There is no difference in the importance and value of activity but this may be due to the novelty of the task.

A number of questions were asked to ascertain the learner's perception of the learning task and the role of the robot. The different conditions appear to have affected the way that learners perceive the robot and if they would listen to the robot in the future. The students in the *SRL_PROMPT* condition felt most like they had performed better in the task than other students. This could be because they were aware of overcoming problems themselves without much assistance and, as discussed above, that perhaps felt a greater sense of achievement in a more 'hard won' context as they also felt some stress due to the lack of assistance when they were aware of their weaknesses. The students in the *OLM_ONLY* condition were aware that the robot was not helping them and consequently felt tense and had a low perception of the robot. Surprisingly, in the *CONTROL* condition, the robot was perceived positively. The robot exhibited exactly the same behaviour as the *OLM_ONLY* condition but as the students were not as aware of their difficulties the robot is perceived as a friend.

The most important finding is that when an OLM is present and the robot fails to help the learner then the robot is not perceived well, and the learner appears to be acutely aware of this lack of assistance due to the inclusion of the OLM. In the *CONTROL* condition where the learner is not as aware of their performance the robot is well perceived even though it does not do anything to support the learner. In fact the robot in the *CONTROL* condition is best perceived in terms of enjoyment, motivation, and being thought of as a friend.

Making the learner aware of their learning shortfalls via an OLM, but not providing specific help, can increase the pressure experienced by the learner, as the learners reported higher levels of pressure in the *SRL_PROMPT* and *OLM_ONLY* conditions. Some pressure and tension is good for learning as it will prompt the learner to take some action, however too much pressure could cause the learners to become disengaged. In this study the *SRL_SCAFFOLD* helps relieve pressure by suggesting appropriate strategies that the students could apply, and this would appear to be an appropriate level of scaffolding. In the *CONTROL* condition that less pressure was felt. This may be because of a lack of awareness of issues or a combination of this and a greater social bond with the robotic tutor, which has not led to as great a learning gain.

All students found that the activity had importance and value regardless of the condition. This may be the novelty effect of the robot. Learning improvements were observed for all students. This indicates that there is no difference in levels of motivation between the conditions, and that the learning gain is down to learners working more effectively to achieve their learning gain. The key results are summarised below:

- A higher level of personalisation and adaptive scaffolding of SRL seems to lead to greater adoption of SRL behaviours and an increase in learning gain.
- OLM alone can be beneficial for less able students but loses its effectiveness with more able students, this may be because more able students are already aware of their skills and can use trial and error to arrive at their learning objectives.
- Adaptive SRL scaffolding has a greater impact on more able students and may assist them in attaining higher learning gain.
- Without any SRL support in the control condition, learners do not appear to engage many SRL processes.

- If the robot is present with an OLM it should offer some support to assist the learner. Otherwise the learner will perceive the robot poorly and may not follow its advice in the future.

- Perceiving the robot highly as a friend may motivate the students to engage in the learning scenario, however this does not necessarily foster SRL processes; appropriate scaffolding must still be made available.

This study shows the importance of how the robot's behaviours can be perceived within the context of the activity and the importance of finding a balance between appropriate social support and SRL support to successfully scaffold SRL skills. Social support is essential for reducing pressure and tension and supporting engagement in the activity. It appears from the results that in the case of the control condition that the robot is perceived as a friend due to its behaviour being non judgemental, however, this same behaviour in the OLM condition is seen as unhelpful. This is a new finding in OLM research as no other research uses a pedagogical agent and OLM a similar way.

The different robotic behaviours in the static and adaptive SRL conditions may make the robot seem more like a teacher or classmate but appear to offer enough social and SRL support to reduce pressure and tension but still allow the learner to push themselves and learn. This shows how important social interaction such as encouragement or supportive interaction is to the development of SRL. It could also be argued that the personality of the robot must match the role that the robot plays to the learner. If the robot has an overly social personality in a tutoring role then it may in fact harm the performance of the user (Kennedy et al., 2015). This is an example how a social robot tutor could be argued to have as a basis the socio-constructivist approach to learning, where the cognitive development of the individual is supported by social interaction (Tongchai, 2008). It is believed that socially assistive robots can support the best practises of socio-constructivist learning theories (Clabaugh et al., 2015), which may lead to the adoption of SRL skills. For example, adoption of good SRL processes can be influenced by members of a social network in a learning planning application (Lin et al., 2015).

It may be that SRL scaffolding of a less social nature may have been effective coming from on screen prompts or a virtual agent as with ITS research (Koedinger et al., 2009). It was decided not to compare virtual to physical feedback as it has been shown before that a physical embodiment is preferred to a virtual embodiment (Leyzberg et al., 2012), and learners prefer explanations of a simple OLM via a robotic tutor rather than text based explanations displayed on-screen (Jones et al., 2014b).

It is possible that other forms of scaffolding SRL that are not based upon an OLM would be effective, e.g. providing SRL prompts when an OLM was not present. An OLM was chosen as it is one of the most effective ways to show the learner their developing skill levels and assist them with reflection. Alternatives might have been to allow other mechanisms for reflection in the activity such as skill diaries (Long and Aleven, 2013a) or other note taking tool (Sabourin and Lynne, 2013).

6.2.6 Summary and conclusions

This paper explores how personalised tutoring by a robot achieved using an OLM promotes SRL processes and how this can impact learning in primary school children. The results show that more personalised and adaptive scaffolding leads to a greater indication of SRL processes and higher learning gains. There are significant differences between the learning gain in the the adaptive SRL scaffolding and the OLM only conditions. The differences are due to the support of SRL behaviour in the conditions chosen in the study. The main benefit of the support given by the robot and OLM in the adaptive SRL scaffold condition is to prompt the learner to reflect and to motivate the students to choose appropriate task strategies. For a learner to engage SRL practises they must be aware that they have issues with the task and also be motivated to engage meta-cognitive processes to fix those issues. The OLM only condition is not enough to make the learners aware of issues. These differences can be seen in the high level indicators of SRL from the task data between the conditions that appears to support this conclusion.

The results support that reflection is a foundation of meta-cognitive process such as SRL. Having access to an OLM appears to have offered benefits over the control condition to less able students. This is in line with other work investigating the impact of OLM in an ITS (Mitrovic, 2007).

Another key aspect is for the robotic tutor to motivate the students to engage in SRL processes. In previous work it is observed that the robotic tutor may increase trust, enjoyment, and understanding in explanations of an OLM as compared to on-screen feedback alone, as detailed in study 3 (section 3.6) (Jones et al., 2014b), which could motivate the students to make more effective use of the feedback. In this work the robot in the adaptive condition appears to be able to motivate the students to use SRL processes with well-placed suggestions. The robot in the static scaffolding condition appears to raise awareness of issues while adding stress to the learner which does not necessarily help in the short-term, however this may help the learners in the long run. In the OLM only condition the students are aware that the robot does not help. The robot in the control group is generally engaging and well-liked by the students but it does little to motivate meta-cognitive processes. This indicates that students do look to the robot for, and would likely, accept assistance.

This study shows the importance of adapting to a learner when scaffolding SRL processes. This reflects the findings from HHI studies where adaptive scaffolding has led to improved learner understanding compared with fixed or no scaffolding (Azevedo et al., 2004). The need to adapt to student's SRL skills is highlighted with more able students, at best static and less personalised scaffolding does not provide any greater degree of support to these learners, at worst it could be dangerous to continue to scaffold basic SRL processes as this support could start to become distracting, less effective, and frustrating for the learner (Greczek et al., 2014). Removing support when it is no longer needed is one of the principles of scaffolding (Lajoie, 2005). Fading or removing scaffolding based on an OLM to assist in problem selection can increase the ability for students to select more appropriate problems (Mitrovic, 2007). Consequently there is a need to be able to model the students' SRL skills to be able to decide when to reduce the SRL scaffolding.

There are open questions around adapting to the learners meta-cognitive state, finding appropriate social behaviours for the robotic tutor, and investing the scaffolding of SRL in longer-term studies. This research aims to investigate how a robotic tutor can better adapt to SRL skills, including identifying the factors that can indicate the level of SRL skills possessed by the learner. Based on previous research the indicators of SRL behaviour are pre test scores (Sabourin et al., 2012b), ability at problem selection (Mitrovic, 2007), and the frequency of tool or resource use (Sabourin et al., 2012b). In this study it is observed how important the robotic tutors social behaviours are to the interaction, which is in line with a review of longer-term interactions with robots (Leite et al., 2013), which recommends that a robot should be able to display an awareness of and respond to the user's affective state and also adapt to the individual's preferences in order to build a good social interaction which is essential for longer-term support. This type of longer-term interaction is essential to investigate if this type of SRL scaffolding can lead to long term changes in SRL behaviour, as such changes can be difficult to achieve with an ITS (Koedinger et al., 2009). Examples of more social supportive behaviour would be calling the learner by name, referring back to previous interactions, and commenting on the development of the learner, and other supportive and motivating statements.

In summary, this study indicates that adaptive SRL scaffolding delivered by a social robotic tutor can lead to greater SRL behaviours and learning gains. However, care must be taken with the delivery of SRL scaffolding as highlighting issues but not providing sufficient level of support can make the learners feel higher levels of stress and pressure, which may cause learners to become disengaged.

Based on this study it is believed that reflection and personalised SRL scaffolding are the key drivers behind the learning gain, however, might it be the case that any personalised support would lead to similar learning gains? In the study 6 (section 6.3) the SRL scaffolding used here is compared against more traditional domain scaffolding. In addition, it is unclear if the differences in SRL behaviour observed between the conditions will continue to be adopted in the longer-term, or if the learners only listened to the robotic tutors prompts as the support was a novelty. In the next study the support is investigated over a longer time period.

6.3 Study 6: longer-term SRL study

6.3.1 Introduction

In this section a longer-term study is presented that compares personalised adaptive SRL scaffolding to traditional adaptive domain tutoring, this enables the investigation of the benefits of longer-term SRL scaffolding. With a longer-term study with multiple interactions the robot may be able to effect and detect some change in a learner's SRL behaviour over time. All of the fully autonomous robot behaviours described in subsection 5.2.2 have been used. The evaluation is carried out using the metrics described in section 6.1.

Motivation

The aim is to support the longer-term adoption of SRL skills so that they are adopted as a general behaviour; longer-term behaviour change is also one of the aims in Socially Assistive Robotics (SAR) (Matarić, 2014) research. HRI researchers believe that social robotic tutors can be used to assist in developing skills that can transfer to longer-term behaviour change (Tapus et al., 2007) or generalise to other scenarios and contexts (Begum et al., 2016). Such changes can be difficult to achieve with an ITS (Koedinger et al., 2009) which may be due to the missing social factors.

Robots are increasingly being used to provide motivating, engaging and personalised support to learners (Matarić, 2014). Robotic tutors have been able to increase learning gain by providing personalised hints (Leyzberg et al., 2014) or personalised problem selection (Gordon and Breazeal, 2015). Most research in the area has investigated the use of robotic tutors to increase students' learning gains and engagement. However, in the study described in section 6.2 it was shown how personalised adaptive SRL feedback can increase learning gain and how it may be possible assist children in developing SRL skills with a robotic tutor. While short-term studies (e.g. a single session) are relatively common (Leite et al., 2013), longer-term explorations (e.g. over weeks or months) of the effects of robotic tutors are still limited in number and scope.

In this study the aim is to investigate the longer-term effects of the personalised adaptive SRL support. The approach is built upon the personalised adaptive SRL support described in section 6.2 and (Jones and Castellano, 2018). This type of personalised adaptive SRL support is compared to personalised domain support with an investigation in to longer-term effects of such support. This enables the investigation of how effective the SRL scaffolding is compared to motivating, engaging and personalised domain support alone. In the study described in section 6.2 it was observed that despite feeling engaged and motivated by the robotic tutor the learner's did not engage in SRL processes unless prompted.

The aim is also to investigate the transfer of skills over time with repeated measurements in this longer-term study. This enables the investigation of how the skills developed by a learner can transfer to longer-term behaviour change (Tapus et al., 2007) or generalise to other scenarios and contexts (Begum et al., 2016).

The aim is also to contribute to the field of longer-term of robot interaction, specifically in the area of memory and adaptation where the robotic tutor remembers aspects of the past interactions with users, which has been identified as an unexplored area (Leite et al., 2013). To be effective in longer-term interactions the robot should be able to display an awareness of, and adapt to the individual in order to build and maintain a good social interaction (Leite et al., 2013). One way to build a bond between the robot and learner is to use memory to recall past activities (Leite, 2013). The robotic tutor is able to utilise the learner model as a memory of the learners' development in the current and previous interactions. This enables the robotic tutor to provide summaries of the learners' development through the current session, in the form of a wrap-up at the end of the session and the learners' development over all previous sessions in the form of a summary at the beginning of a session. This wrap-up and summary should support the learners to reflect as described in section 5.2.2. Showing a memory of a learner is also important in establishing a good relationship in a longer-term interaction, as discussed in subsection 2.2.5.

Research questions

The primary research question is: *does longer-term adaptive SRL scaffolding make a lasting improvement on learners' SRL skills and learning gain?* The aim is to contribute to the field of longer-term robot interaction, specifically in the area of memory and adaptation where the robotic tutor remembers aspects of the past interactions with users, which has been identified as an unexplored area (Leite et al., 2013). In this study the robotic tutor provides different levels of personalised SRL scaffolding to primary school children. The autonomous robotic tutor's behaviour builds upon information provided to a student in an OLM. Personalised adaptive SRL support with domain support is compared to personalised domain support alone to investigate longer-term effects of such feedback. This enables the investigation of how effective SRL scaffolding is compared to motivating, engaging and personalised domain support alone.

Additionally it is asked: *how longer-term adaptive scaffolding impacts learners' perception of the robot, activity, motivation, SRL skills, and learning gain?* With this question the aim is to investigate the longer-term effects of personalised SRL scaffolding on the user experience.

Hypothesis

The hypothesis is that a personalised and adapted scaffolding of SRL processes via OLM will lead to higher learning gain and improving SRL processes over a robot that only supports domain skills. There may not be a huge increase in learning gain in the adaptive SRL condition over domain tutoring as the learners will still have personalised domain support. However, the hypothesis is that more SRL behaviours, as identified in the short-term SRL study (section 6.2), will be evident and this should lead to better allocation of effort and more effective learning.

Similarly, the hypothesis is that there will be little difference in overall motivation and engagement. In the previous study described in section 6.2 it was observed that students felt engaged and motivated by the robot even when it did not assist them in the control condition. As both conditions offer personalised support, then the robot should offer similar levels of motivation and engagement overall. There may be slight differences in the perception of the robot, although this may be focused around the role; i.e. the robot in the SRL condition may be perceived more as a teacher, as the support offered will prompt the learners to take more responsibility. It is believed that the robot will be well perceived in both conditions as it will always help the learners. More specific hypothesis are detailed in section 6.3.2.

6.3.2 Method

The aim is to investigate how personalised SRL scaffolding via OLM with a social robotic tutor impacts learning gain, SRL processes, and transfer of longer-term SRL skills. To achieve this a longer-term study is conducted with 2 conditions. In the control condition the robotic tutor provides personalised domain support. In the SRL Scaffolding condition the robotic tutor provides SRL scaffolding, in addition to the domain support, based on the learner's skill levels, task performance, and rules for appropriate SRL behaviour. This study is a between subject design. 24 primary school participants individually interacted with the robot in 4 sessions - 1 session each week, over a period of 1 month (detailed in Table 6.4). An overview of the scenario is shown in Figure 6.26

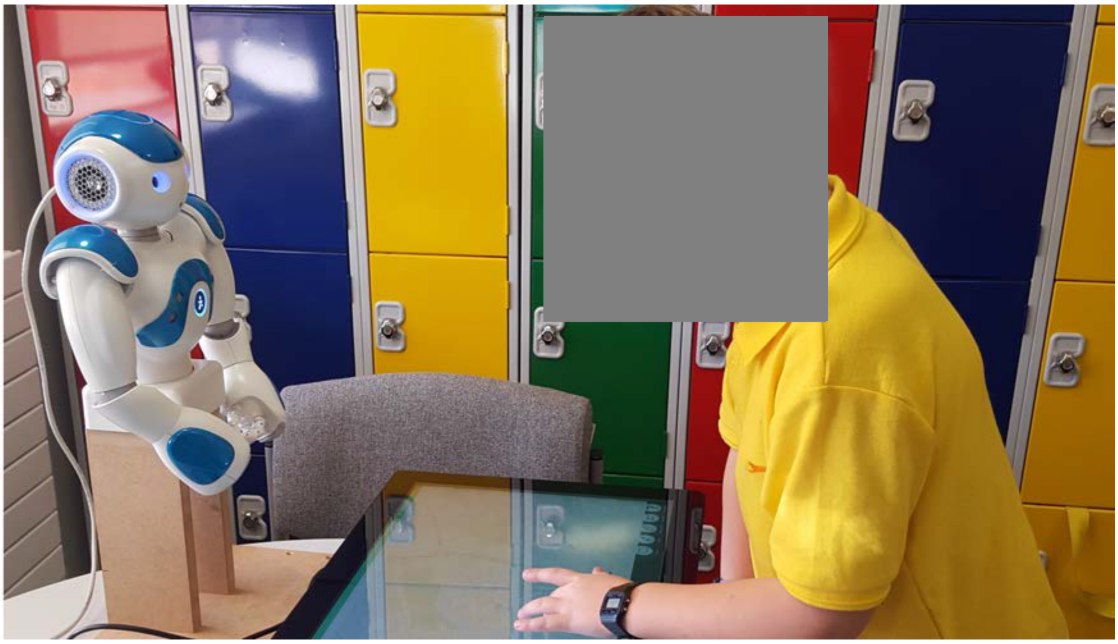

Figure 6.26: Study 6: longer-term SRL study scenario

Participants

Schools and teachers were approached and recruited as described in subsection 3.3.1, where the aims of the research project were described to the schools and teachers. There were 24 (10 female, 14 male) participants of mixed ability. The learners were aged between 10 and 12 and attended the same primary school in the U.K. The robot is fully autonomous and begins by providing the introduction and summary, offers support to the learner throughout the learning task, and provides a wrap-up at the end of each session. In accordance with the ethics procedure, informed consent was obtained in writing from the parents and the children participating in the study as outlined in subsection 8.1.2. [redacted]

Procedure

The teachers were emailed the learning activity in advance. Prior to the session with the robot the teachers were asked to allow all of the learners in the class to take part in the activity. The author also gave a presentation at the school about the study. The learners that wanted to participate were given consent forms and information sheets to take home for parents approval.

The study was conducted in the participants' primary school. The students were asked to complete a pre-activity domain test and SRL self-report questionnaire. The participants individually interacted with the robot in 4 sessions - 1 session each week over a period of 1 month. In each session the autonomous robotic tutor introduced the learning task and explained how the task and tools work. Each student then carried out the task which was limited to 20 minutes in each session. At the beginning and end of each session the students were asked to rank their distance, direction, and symbol skills. After all 4 sessions each student was then asked to complete a post-activity domain test and a questionnaire with questions regarding their perception of the robot and the learning scenario. This is shown in Table 6.4.

Experimental setup

As with study 5 (section 6.2), a fully autonomous Aldebaran Robotics NAO torso was used as the robotic tutor. The robot acted in the role of a robotic tutor and social agent. In both conditions the robot provides domain tutoring, introduces the learning task, tools, and performs idle motions throughout the session. The activity

Table 6.4: Procedure details for study 6: longer-term SRL study

Week	Activity	Notes
1	Overview	Presentation to class to get learners interested in working with the robot
1	Pre-tests	Domain pre-test (section 8.5.3) and SRL pre-test (section 8.5.1)
2	Session 1	
3	Session 2	Introduction of map trail task
4	Session 3	Introduction of SRL task
5	Session 4	
6	Debriefing	Domain post-test (section 8.5.3), questions about robot and task (subsection 8.5.2), and SRL post-test (section 8.5.1)

runs on a 27 inch touchscreen table. The learners were standing up to enable them to comfortably reach all areas of the touchscreen. The robot was positioned on a stand opposite the touchscreen in order for it to be at a similar height to the learner. The setup is shown in Figure 6.26 and Figure 6.27.

The task

The autonomous robotic tutor supported individual learners in a geography task, the learning task is described in detail in section 4.2. The task enables the learner to exhibit SRL skills and processes, i.e. self-monitoring, goal setting, and help seeking. The learner is in total control of the task at all times, which is in line with the methodology of scaffolding and moving from external regulation to self-regulation where the learner is allowed to practice and develop their SRL skills. The activity was designed to test compass reading, map symbol knowledge, and distance measuring competencies.

The task gives basic 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. The learner was provided with three tools to assist them with

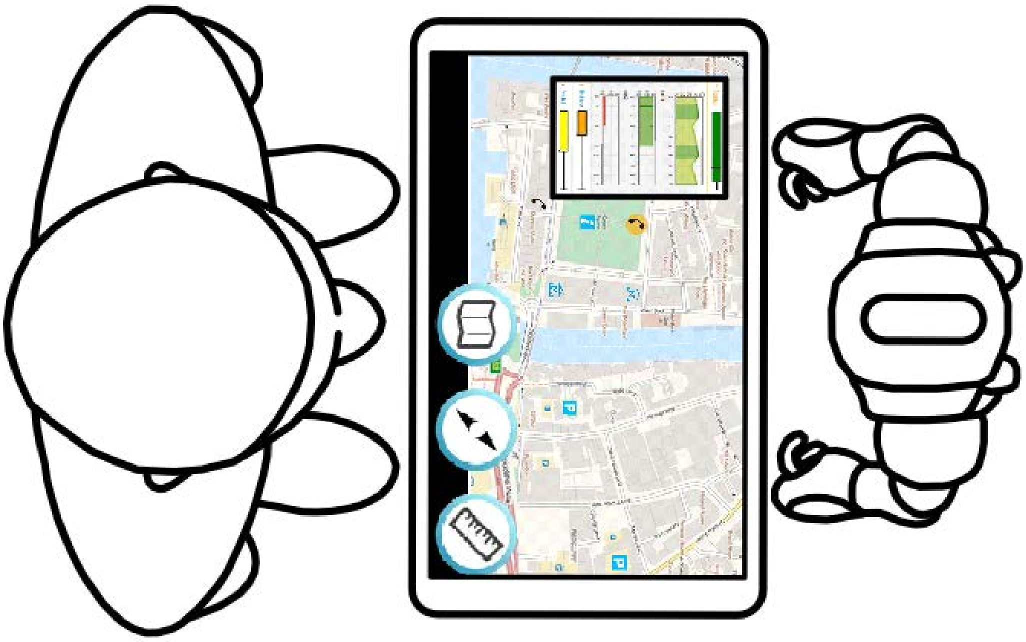

Figure 6.27: Setup for study 6: longer-term SRL study

the activity. They had 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 learning task builds upon the task described in study 4 (section 3.7) and study 5 (section 6.2). Due to the 4 sessions in this longer-term study the number of activities available has been expanded.

In session 1 there were 6 activities: cardinal directions (easy compass); inter-cardinal directions (harder compass); distance in meters; distance in km (harder distance as it requires conversion from m to km); symbol; and all skills (compass, distance, and symbol combined). In session 2 a map trail activity was added that combines all skills. In session 3 a wind farm activity was added that requires the learner to use distance and symbol skills to solve the problem of where to place a wind farm. For completeness, there was no new activity in session 4. Tasks were introduced gradually so that the learner was not overwhelmed by choice in the beginning and could become familiar with the activity. This procedure is detailed in Table 6.4. Tasks were introduced gradually so that the learner was not overwhelmed by choice in the beginning and could become familiar with the activity.

Learner model and OLM

A learner model is built as the basis for the robotic tutor's domain support in addition to the SRL scaffolding behaviour and OLM skill meters used in the SRL condition. The learner model were the same as described in study 4 (section 3.7) and study 5 (section 6.2). The learner model is described in detail in section 4.3.

The OLM allows the student to see a visualisation of the learner model that the student can understand their developing skills and identify areas where they have strong or weak knowledge. 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 (Long and Aleven, 2013b). 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. The OLM is described in detail in section 4.4.

Robotic behaviour

There are a number of events that can trigger the robot to execute a behaviour, these are: Answer attempt, when the learner answers a step in the activity; Timeout, when there has been no robot or learner activity in the preceding 15 seconds; and Tool selection, when the learner selects a tool to use. When one of these events occurs the system evaluates if the robot should execute a behaviour according the condition (Table 6.5). To avoid repetition or the robot talking too much there are alternative phrases for the robot behaviours and an utterance is not executed if that utterance has been delivered by the robot recently.

Domain tutoring

In both conditions the robotic tutor offers domain tutoring. The aim of domain tutoring is to provide support to the learner throughout the task, to keep them motivated, and keep them progressing through the learning task. The pedagogical support has been developed based on UCD studies and a review of literature detailed in section 4.6.2.

Below is a brief summary of the robot's behaviours in this context. When the learner answers correctly the robot will provide positive feedback in the form of a positive beep. When the learner answers incorrectly the robot will in the first case repeat the instructions or keywords for the objective. If the learner continues to make mistakes the robot will provide more detailed domain support, this may take the form of motivational feedback, i.e. such as saying "almost", highlighting the aspect of the step that is incorrect (i.e. pump feedback), or give hints of how to solve the problem by offering keywords or a strategy to try to solve the problem. The help provided is based on the learner model and the performance that step. More detailed help is given if the learner model value is low and there have been multiple incorrect attempts. More motivational support will be provided if the learner model is high and there have been few errors.

SRL scaffolding

In the SRL scaffolding condition the robot offers SRL scaffolding in addition to the domain support. 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 weaknesses so that they can effectively plan their learning through selecting appropriate strategies, goals, activities, and using the tools and resources available.

The autonomous robotic tutor provides adaptive scaffolding whereby the learner is prompted to use SRL skills at appropriate points in the activity based upon the learner's state (Azevedo et al., 2004; Koedinger et al., 2009). To support this an ideal model of SRL has been developed for the learning context described in section 5.2. Such an approach has been used in another meta-cognitive tutoring system that focuses only on when the student should ask for help (Aleven et al., 2006).

The robot's SRL scaffolding behaviours to promote good SRL behaviour are detailed in Study 6: adaptive SRL study - robot behaviour and triggers for each condition (Table 6.5) and Study 6: adaptive SRL study - robot behaviour and triggers for each condition continued (Table 6.6). For more details the SRL scaffolding procedures are described in section 5.2 and were also used in study 5 (section 6.2).

These robot behaviours, gestures and speech, are based on recordings from study 4 (section 3.7). It was observed that teachers scaffold SRL skills by drawing attention to the learner's developing competencies, 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 (Jones et al., 2015b), e.g. teachers would encourage the students to work on the more simple activities until they are proficient before encouraging the student to work up to more advanced activities. This approach is used as the basis for the robotic tutor's behaviours.

The robot uses the OLM to prompt the learner to reflect on their developing skills, and also as a basis to suggest other SRL skills, e.g. the robot will prompt the learner to reflect on their skills and mastery of the current activity, to prompt the learner to develop appropriate task strategies, and to work on an activity of an appropriate difficulty level for learning. In the SRL scaffolding condition 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 (Long and Aleven, 2013b). 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. This enables the learner 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 helping them identify knowledge gaps, based on this they can then fill their knowledge/skill gaps by selecting an appropriate activity or tool.

It is hoped that the SRL scaffolding from the robotic tutor and OLM will improve learners' ability to self-assess their performance. This meta-cognitive skill also allows the student to assess the difficulty of the problem that they are working on, and to decide to continue with the activity or move on (Mitrovic and Martin, 2002).

As this study is longer-term there is the possibility to provide a wrap-up of the completed session and a summary of previous sessions when introducing the later sessions in the study. The robot uses these points to discuss the learners' developing skills in terms of their competencies, tool use, performance, and mastery of the activities. It is hoped that this will prompt the learners to reflect more on their developing skills and performance. The summary and wrap-up are detailed in section 5.2.2.

If SRL scaffolding is effective then students should engage in appropriate SRL processes in the learning task. High level indicators of SRL were identified for this learning context in study 5 (section 6.2).

Students with higher levels of SRL skills should work on *problems of the appropriate difficulty*. If the problem is too easy they should move on, if the problem is too hard they should either seek to address the issue or switch to an easier activity to master the skills required, this will show an awareness of appropriate goal setting for either process or outcome goals. A high SRL skill level student may also take *more time over each question* as they will work on questions that are at the edge of their ability. The high SRL students will not necessarily have more questions correct on average, or even in total, as they should be pushing their zone of proximal development. The ability to reflect and self-assess knowledge and skills is linked with the *number of attempts* to get a question correct, learners with high levels of SRL skills should realise quickly that they have an issue, and promptly correct the problem, so a high level of SRL skills will have a *low average number of attempts at each problem*.

High levels of SRL should also lead to *appropriate tool use*. High SRL students will not necessarily have high tool use, as they may not need a tool at all; however, when a learner with high levels of SRL uses a tool it should be appropriately targeted. Students using SRL skills will be aware of the OLM increasing and decreasing and how incorrect questions will affect this. Consequently, students should be aware when there is a gap in skill or knowledge and work to address the problem quickly. The higher levels of SRL should lead to increased *learning gain* as the learners should have better allocated their efforts.

Conditions and hypothesis

There are two conditions to explore the hypothesis. In all cases the robotic tutor is present and provides domain tutoring and gives an introduction to the task and the tools. The different robot behaviours and the events that trigger them are summarised in Table 6.5 and Table 6.6.

SRL condition. In this condition the autonomous robotic tutor 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 (i.e. the ideal model). This is considered 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 (Koedinger et al., 2009). There is additional SRL or reflective support, given at the beginning and at the end of each session, where the robot gives feedback on the learners skill levels, tool use, and mastery of activities.

Control condition. In this control condition the robot provides domain support as described in the above section (section 6.3.2). The learner does not receive full SRL support or have access to the OLM, this is to try and limit the amount of meta-cognitive support. However, there is some support SRL in the structure of the activity, and specifically for motivation as part of the domain tutoring, the learner is also informed if the answer that they have provided is correct or incorrect.

In all conditions the robot introduces the learning task, tools, and performs

Table 6.5: Study 6: adaptive SRL study - robot behaviour and triggers for each condition

Triggers	Description	**SRL**	**CONTROL**
S1 Introduction			
Intro	Greet learner by name and give overview of tools and activity menu	X	X
S2 - S4 Introduction and summary			
Intro	Greet learner by name and give overview of tools and activity menu, introduce new activity	X	X
SRL Intro	List of skills that are high	X	
SRL Intro	List of skills that are low	X	
SRL Intro	List of activities that are mastered in previous session	X	
SRL Intro	Summary of tool use in previous session, You used the tools well last time/You used the tools well but also when you did not really need to/You did not use the tools to help last time	X	
Wrap-up (every session)			
Wrap-up	Goodbye	X	X
SRL Wrap-up	List of skills that are high	X	
SRL Wrap-up	List of skills that are low	X	
SRL Wrap-up	List of activities that are mastered in previous session	X	
SRL Wrap-up	Summary of tool use in previous session, You used the tools well last time/You used the tools well but also when you did not really need to/You did not use the tools to help last time	X	
Correct answer (every session)			
Correct	Positive beeping and gestures	X	X
Timeout/Correct - Activity is mastered	Well done, you have mastered this, shall we move on?	X	
Timeout/Correct - Activity not mastered	Let's keep going we have not covered everything	X	

Table 6.6: Study 6: adaptive SRL study - robot behaviour and triggers for each condition continued

Triggers	Description	**SRL**	**CONTROL**
Incorrect answer (every session)			
Incorrect	Sympathetic beeping and gestures	X	X
Incorrect	Domain help	X	X
Timeout/Incorrect - Activity not mastered	Let's keep going we need to focus on south	X	
Timeout/Incorrect - Activity not mastered	We need to focus on south; is there a tool that can help?	X	
Timeout/Incorrect - Activity not mastered	We need to focus on south; should we do an easier task?	X	
Timeout/Incorrect - Activity not mastered	Should we do an easier activity?	X	
SRL scaffolding of tools (every session)			
Appropriate tool selected	This tool should help!	X	
Inappropriate tool selected	Is there another tool that can help you?	X	
Inappropriate tool selected	You know this! Do you still need the tool?	X	
Timeout	Is there a tool that can help you?	X	
Timeout (every session)			
Timeout	Domain help if applicable	X	X
Timeout	Let's look at the evidence to see what you should focus on?	X	
Timeout	What is it asking you to do this time?	X	
Timeout	It can be enjoyable when you figure out hard problems	X	
Timeout	What could help you understand this problem	X	
Timeout	Do you think it is important to do well?	X	
Timeout	Just keep going and we can see if you are right or wrong	X	
Timeout	You have got most of the questions correct for this activity	X	
Idle behaviours (every session)			
Continuous	Idle behaviours	X	X

idle motions throughout the session as described in detail in section 4.6.2 and section 4.6.2.

The hypothesis is that a personalised and adapted scaffolding of SRL processes via OLM will lead to higher learning gain and improving SRL processes over a robot that only supports domain skills. There may not be a huge increase in learning gain in the adaptive SRL condition over domain tutoring as the learners will still have personalised domain support. However, the hypothesis is that more SRL behaviours will be evident and this should lead to better allocation of effort and more effective learning. The specific hypotheses are as follows:

Hypothesis 1 (H1). Adaptive SRL and domain scaffolding will lead to a greater increase in learning gain than domain scaffolding alone.

Hypothesis 2 (H2). Adaptive SRL and domain scaffolding will lead to more appropriate SRL learning behaviour than domain scaffolding alone.

Hypothesis 3 (H3). Adaptive SRL and domain scaffolding will lead to an increase in self report of SRL motivation than domain scaffolding alone.

It is expected 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 (Mitrovic, 2007) and the findings in study 5 (section 6.2).

A number of questions are asked in the post-activity questionnaire based on the IMI (McAuley et al., 1989; Ryan, 1982), as the differences in the robot's behaviour between conditions may impact the perception of the robot and the task.

Hypothesis 4 (H4). The perception of the robotic tutor will differ between activities. The robot's behaviour will affect the learner's perception of the robot, the role of the robot, and the learner's attitude towards the robot.

Hypothesis 5 (H5). The perception of the activity will differ between conditions. The robot's behaviour will affect the learner's perception of their competence in the activity, the importance/value/interest in the activity, and the perception of the OLM skill meters.

Data collection

The task recorded all interactions with the touchscreen to a log file and database. A domain pre-test questionnaire and the SRQ-A was given to the learners before the session. These are detailed in section 8.5.3 and section 8.5.1. A domain post-test, a questionnaire about the learner's experience with the robot and task, and the SRQ-A was given to the learners after the learning session. The post-domain test is detailed in section 8.5.3. The questions asked in the post-activity questionnaire are based on the IMI (McAuley et al., 1989; Ryan, 1982). This is described in detail in subsection 6.1.1 and subsection 8.5.2. These questions aim to investigate how the differences in the robot's behaviour affected the perception of the robot and the activity. Specifically, if there were differences in the learner's enjoyment, engagement with the activity and the robot. Additionally they seek to investigate if the learner could perceive the robot's understanding of the learner. The questionnaire was in the form of a series of Likert style questions. Before and after each session the learners were asked to rank their skills for each competency in the activity, this is described in section 6.1.2. Due to the location of the study setup it was not possible to record audio and video

6.3.3 Results

Data Analysis

The results presented here are derived from the analysis of the log data, domain pre-test and post-test, and questionnaires. Counts of events from log data was extracted by querying the database and processing of the log file. The event counts, domain test results, and questionnaire responses were then entered into SPSS for the analysis described below.

The analysis is broken down to investigate differences between more able and less able students based on the mean of the pre-test domain score, as has been done in other OLM research (Mitrovic and Martin, 2002; Mitrovic, 2007). The breakdown of ability is presented in Table 6.7.

Table 6.7: Participant details for study 6

Condition	Total	Less able	More able
SRL	12	6	6
CONTROL	12	5	7

Significant differences (lower than 0.05) between conditions are highlighted with a connecting black line in the figures below.

Learning gain

The learners were asked to complete a domain test (section 8.5.3) in the week before the start of the study. The learners were then given a very similar test (section 8.5.3) in the week after the 4 week study. Learning gains were calculated using Normalised Learning Gain (Hake, 2002), based on the difference between the pre-activity domain test and the post-activity domain test, the calculation is presented in Figure 6.1 and described in section 6.1.2. In both the pre and post test the learners were asked 20 similar questions that cover compass reading, distance measurement, and map symbols. A t-test was used to determine whether there was any statistically significant difference between the Normalised Learning Gain of the groups. The results are shown in Figure 6.28. In both conditions there is an increase between the pre-test and post-tests, however no significant differences were found.

Adherence to ideal model of SRL

As discussed in section 6.1.2 it is of interest how well learners adhere to the ideal model of SRL. In this section the rates of adhering to or deviating from the ideal model of SRL developed in subsection 5.2.1 are investigated, and how these change

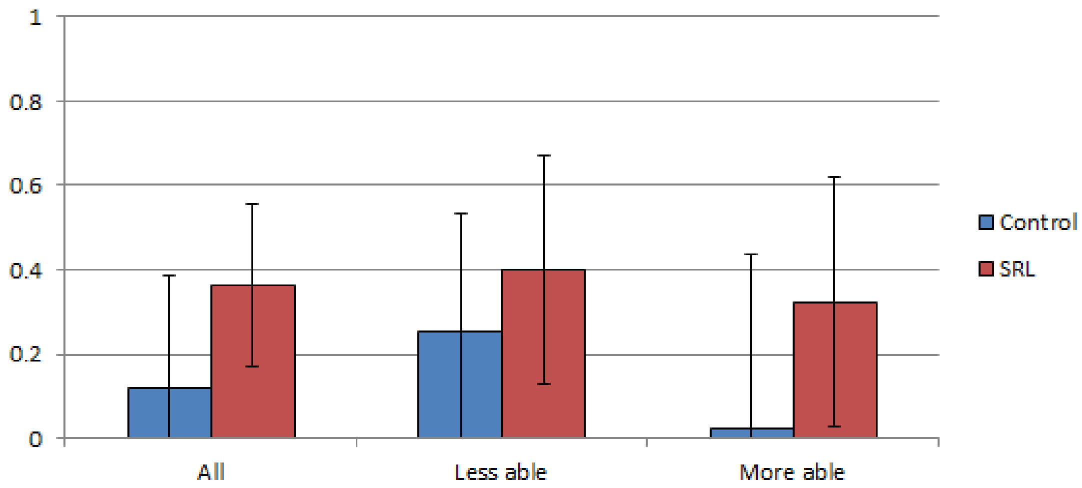

Figure 6.28: Normalised Learning Gain: all learners (left), less able (centre) and more able students (right)

over the sessions. It is hoped that an increase in the adherence to the model and a reduction in deviation over the sessions will be observed as this will indicate that a learner is developing SRL skills. If the learner does not deviate from the ideal model of SRL then the robotic tutor will no longer be co-regulating SRL and the learner will be fully self-regulated. This type of investigation provides an insight into SRL behaviour change over time.

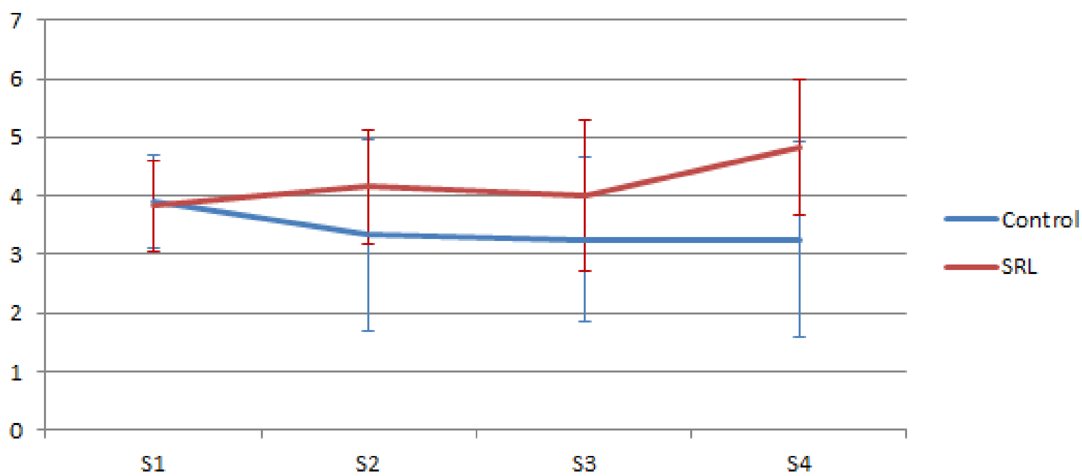

Figure 6.29: Adherence to ideal SRL model: average moves to a more difficult activity when an activity is mastered in each session

Adherence to ideal SRL model: moving to a more difficult activity

when an activity is mastered. The chart in Figure 6.29 shows the average number of times the learners in each condition follow the ideal model of SRL by moving on to a more difficult activity when the current activity is mastered in each session. The *SRL* condition learners on average have a higher adherence to the model and this increases over the sessions. The learners in the *CONTROL* condition have a lower adherence to the ideal model and do not improve throughout the sessions. However, this is not statistically significant.

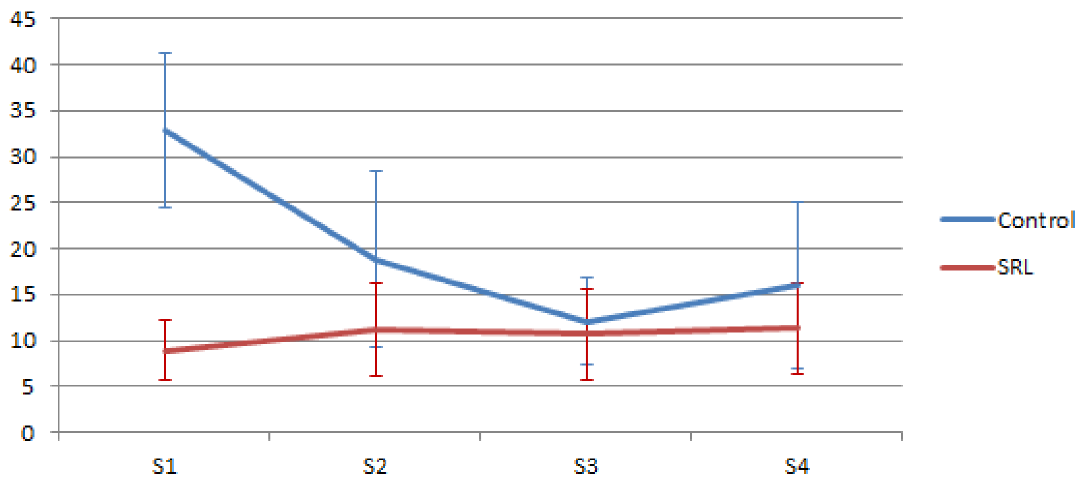

Figure 6.30: Deviation from ideal SRL model: average count of continuing with an activity that is mastered in each session

Deviation from ideal SRL model: continuing with an activity that is mastered. The chart in Figure 6.30 shows the average number of times the learners in each condition deviate from the ideal model of SRL and continues to work in an activity that they have mastered in each session. A high number here means that the learner is deviating from the ideal model of SRL spending time practising an activity that they have already mastered. The learners in the *SRL* condition deviate from the model less frequently than the learners in the *CONTROL* condition. This shows that the learners in the *SRL* condition consistently move on more quickly to a more difficult activity when they have mastered the activity they are working on. There is an improvement in the *CONTROL* condition which shows that the learners are showing some awareness of their developing skills and move on eventually. However, this is not statistically significant.

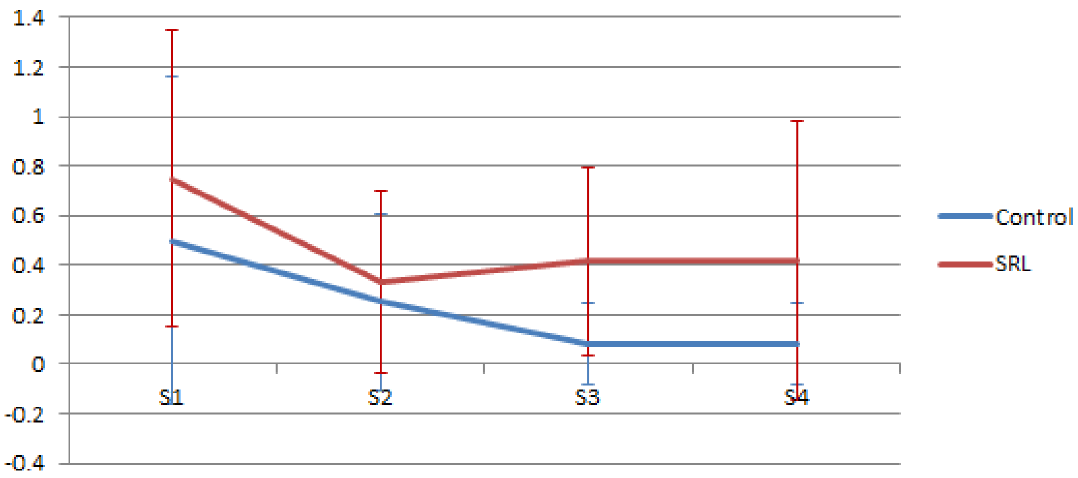

Figure 6.31: Deviation from ideal SRL model: average count of changing activity where there are issues with knowledge/skill in each session

Deviation from ideal SRL model: changing activity where there are issues with knowledge/skill. The chart in Figure 6.31 shows the average number of times the learners in each condition deviate from the ideal model of SRL by changing the activity when there are issues with knowledge/skill in each session. This means that the learner moves to a different activity when they have a low learner model level or have a specific issue with a part of an activity. In both conditions this deviation is rare and the deviations reduce over the sessions. The learners in the *CONTROL* condition do appear to deviate less that the learners in the *SRL* condition but this is also related to the *CONTROL* condition learners spending a greater amount of time in each activity practising when they have already mastered the activity. However, this is not statistically significant.

Deviation from ideal SRL model: moving on from an incomplete activity. The chart in Figure 6.32 shows the average number of times the learners in each condition deviate from the ideal model of SRL by moving on from an incomplete activity in each session. This is a deviation from the ideal model as the learners have not learnt everything that the activity has to offer. The learners in both conditions deviate fewer times on average as they go through the sessions. In

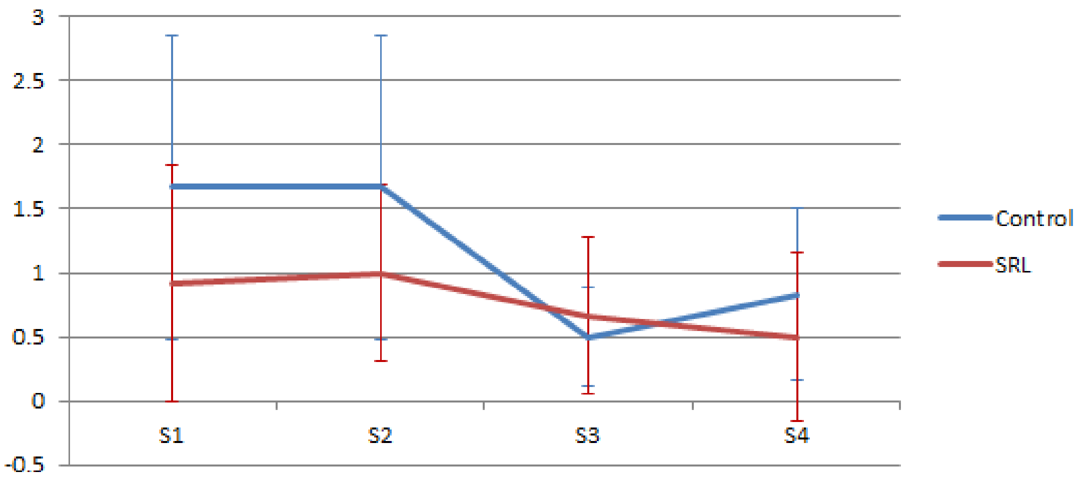

Figure 6.32: Deviation from ideal SRL model: average count of moving from an incomplete activity in each session

general the *SRL* learners deviate from the model less frequently. However, this is not statistically significant.

In summary, in general in the *SRL* condition there is greater adherence to the ideal SRL model as the learners in the *SRL* condition are more likely to move on to more difficult activities when they have mastered the current activity, they deviate from the model less by spending less time in an already mastered activity, and they do not typically change activity until they have learnt all they can from it and resolved all issues with knowledge/skill.

SRL indicators in task performance data

The indicators extracted from the logs aim to measure SRL behaviours that were identified in the previous study (section 6.2) in this learning scenario. Independent samples t-tests were performed on the indicators.

Number of questions answered. This 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. Also a student that is stretching themselves and working on items that they have difficulty with should take longer to provide

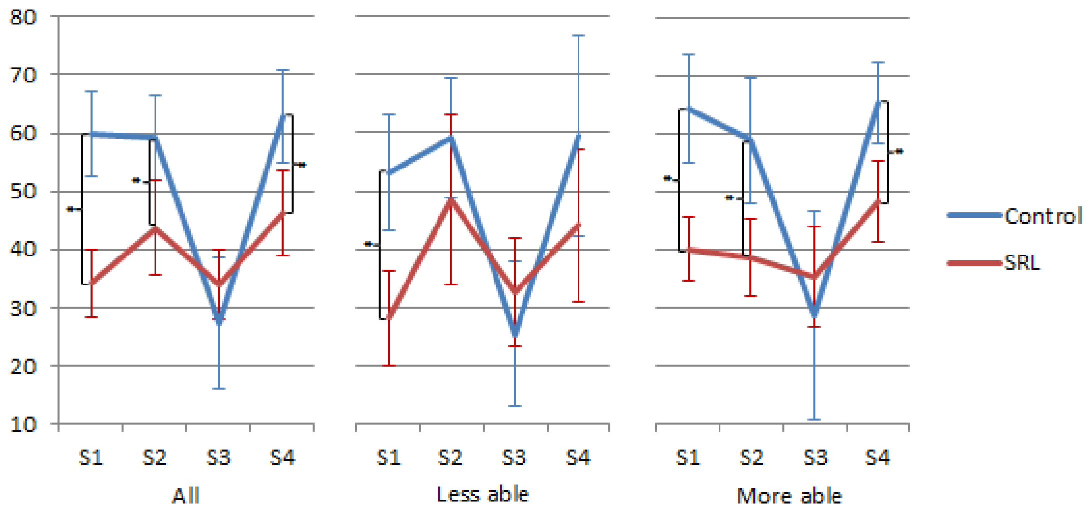

Figure 6.33: Total questions completed in each session: all learners (left), less able (centre) and more able students (right)

an answer.

Figure 6.33 shows that in all sessions other than session 3 there are significant differences between the conditions. In the *SRL* condition learners answer significantly fewer questions than the *CONTROL* condition.

In session 1, the *SRL* condition learners (overall, less able, and more able) answer significantly fewer questions than the *CONTROL* condition learners. In session 2, the *SRL* condition learners (overall and more able) answer significantly fewer questions than the *CONTROL* condition learners. In session 3, there are no significant differences due to the new wind farm task that was introduced that week. However, there were more questions for the *SRL* condition, this may be because the nature of the new task was more supported by the *SRL* condition tutor. It was therefore expected that the number would be low and the learners effectively transfer some of their SRL skills as hoped (see below for further discussion). Again in session 4, the *SRL* condition learners (overall and more able) answer significantly fewer questions than the *CONTROL* condition learners. This indicates that in general the learners in the *SRL* condition are spending more time reflecting on each question.

Ability in session 3 activity. A task was introduced in session 3 that was intended to test the transfer of SRL skills into a slightly different context. The task requires the learner to choose the location of a new wind farm and requires the learner to apply the distance, direction, and symbol skills in a slightly different and more advanced context, the learners that are successful here will have more SRL skills. Figure 6.33 shows that in the *SRL* condition learners were less negatively impacted by the change in activity. This indicates that they are able to successfully transfer some of their SRL skills into this new activity type.

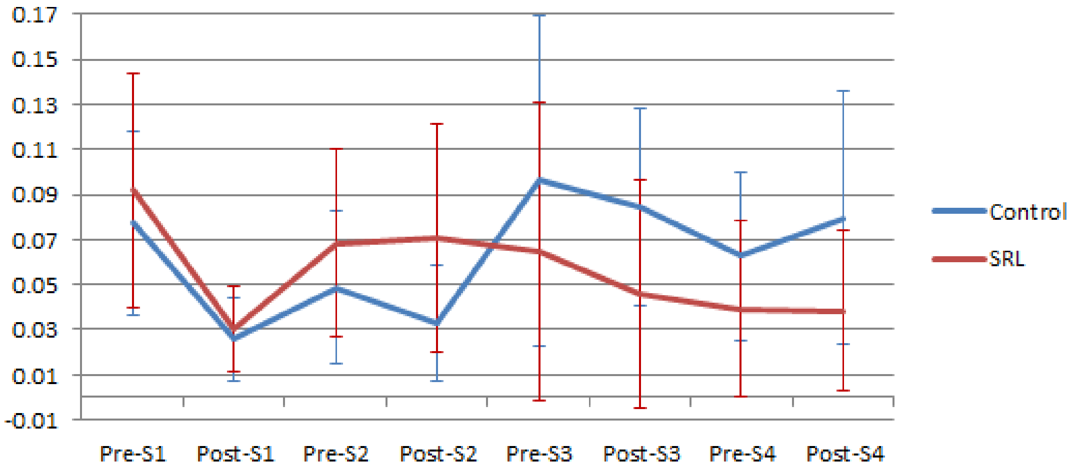

Figure 6.34: Self-assessment accuracy in each session

Self-assessment accuracy. As discussed in section 6.1.2, students with high SRL skills are able to make more accurate self-assessments. Before and after each session the learners were asked to rank their skills for each competency in the activity. The self-assessment accuracy is calculated by comparing the self-assessment to the values in the learner model. The calculation is shown in Figure 6.2 to calculate the self-assessment accuracy or absolute accuracy index. The closer this figure is to 0 the higher the self-assessment accuracy. It can been observed in Figure 6.34, that in general the self-assessment accuracy of the learners in the *SRL* condition improves over time. This is due to the more able students becoming more accurate with their self-assessments.

SRL questionnaire scores

The learners were asked to complete the SRQ-A (Ryan and Connell, 1989) prior to and after the study, (describe this in detail in subsection 6.1.2 and section 8.5.1). This is an instrument that is designed to measure SRL skills of children in an academic context (Ryan and Connell, 1989). The instrument is composed of four sub-scales: external regulation, introjected regulation, identified regulation, and intrinsic motivation.

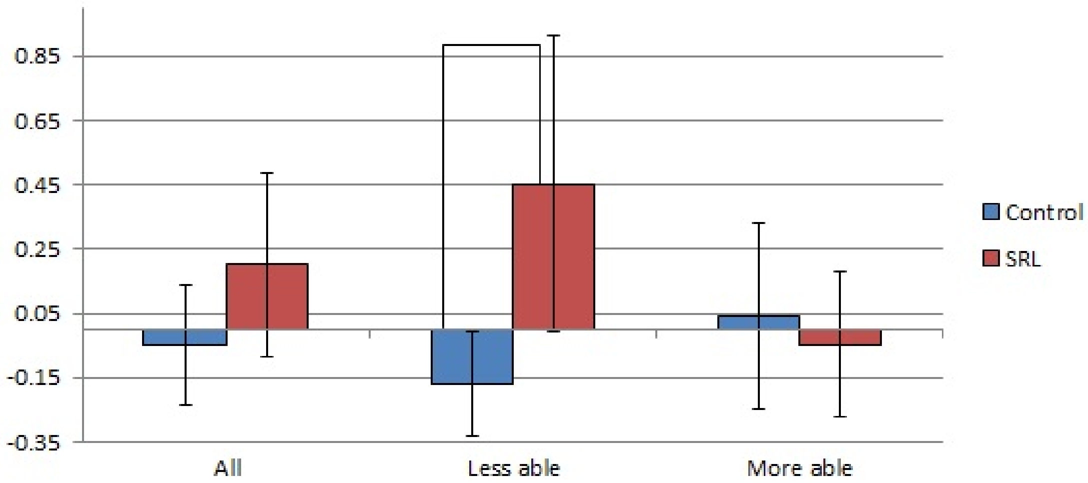

Figure 6.35: Difference in identified regulation: all learners (left), less able (centre) and more able students (right)

Less able students in the *SRL* condition have a significant increase in identified regulation (Figure 6.35). This sub-scale addresses questions concerning the types of motivations for self-regulation that the robotic tutor aims to foster in the students e.g. a willingness to learn and improve.

It is possible to combine the scores of the sub-scales to create an RAI score. To form the RAI for this instrument the formula in Figure 6.36 is used to combine the sub-scale scores.

The paired t-test for the RAI (Figure 6.37) shows a significant increase in the RAI score between the pre and post-test for the *CONTROL* condition, t(11)=–

$$RAI = 2 \times Intrinsic + Identified - Introjected - 2 \times External$$

Figure 6.36: Relative Autonomy Index (RAI)

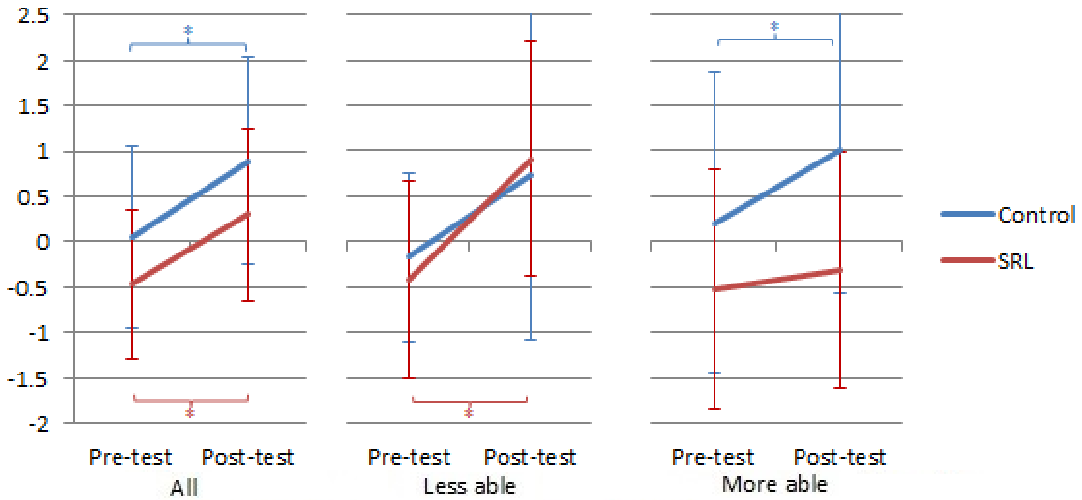

Figure 6.37: Relative Autonomy Index paired: all learners (left), less able (centre) and more able students (right)

2.86; p=0.01, and also a significant increase in the RAI score in the *SRL* condition, t(11)=–2.39; p=0.02. There is an increase in both conditions. In the *CONTROL* condition the more able students also have a significant increase, t(6)=–2.78; p=0.02. In the *SRL* condition the less able students have a significant increase, t(5)=–2.75; p=0.02. In summary the tutoring in the environment appears to improve the SRL attitudes in general.

6.3.4 Discussion

There is evidence to support the hypothesis that a more personalised and adapted scaffolding of SRL processes via OLM can lead to improving SRL processes than domain tutoring alone.

H1, *Adaptive SRL and domain scaffolding will lead to a greater increase in learning gain than domain scaffolding alone*, is not supported; there is an increase between the pre and post-test domain scores for the students in both the *SRL* condition and the *CONTROL* condition. The increase in both conditions is likely due to the domain support offered by the robot in both conditions.

H2, *Adaptive SRL and domain scaffolding will lead to more appropriate SRL learning behaviour than domain scaffolding alone*, is supported; the learners in the *SRL* condition show more SRL indicators, e.g spending more time on each question. In general in the *SRL* condition there is greater adherence to the ideal SRL model than the learners in the *CONTROL* condition. The learners in the *SRL* condition are more likely to move on to more difficult activities when they have mastered the current activity, they deviate from the model less by spending less time in an already mastered activity, and they do not typically change activity until they have learnt all they can from it and resolved all issues with the knowledge/skill. Over the sessions the adherence to the model increases and the deviations decrease for the *SRL* condition learners which shows that the robots scaffolding behaviours will not be triggered as frequently and the learner is moving away from co-regulation of SRL skills to become more self-regulated.

H3, *Adaptive SRL and domain scaffolding will lead to an increase in self report of SRL motivation than domain scaffolding alone*, is not supported; there is an increase in the relevant areas of the SRQ-A questionnaire scores in both conditions. Four types of motivation relating to academic self-regulation were measured; intrinsic, identified, introjected, and external. The sources of the motivation for intrinsic and identified regulation are more internal, and the source of the motivation for introjected and external are more external. There is an increase in the self reported motivation for the overall RAI and the identified regulation, which are the types of motivation that are most important for SRL.

H4, *The perception of the robotic tutor will differ between activities* and **H5**,*The perception of the activity will differ between conditions*, are not supported; as there is no difference in the perception of the robot or the learning task between conditions. This may be because the robot is engaging and motivating due to the personalised feedback in both conditions. This highlights the benefits that personalised *social robotic tutors* in general can have in motivating learners in educational scenarios.

There were no large differences in results between conditions. This may be due to the control condition still providing personalised adaptive support, an opportunity to practice SRL skills, and motivation to the learner throughout the longer-term study. It is believed that had an OLM also been included in the control condition that the results would have been even closer. In previous work that has compared different combinations of SRL support and OLM presence, it was observed that an OLM without robotic support does raise the learners awareness of difficulties(section 6.2) (Jones et al., 2017a), which is in line with other OLM research.

A larger difference may have been evident between conditions by comparing the SRL condition to a control condition that provided less personalised support, however this would not be a fair comparison as the importance of personalised support has been seen in many studies as detailed in the related work section. The most similar study would be that of a social robotic tutor was able to effectively support appropriate help-seeking behaviour by adapting to the learners help-seeking behaviour compared to a control condition that offered help on demand (Ramachandran et al., 2016). It has been observed in the earlier research (section 6.2) (Jones et al., 2017a) that non-adaptive or less personalised support is not as effective.

The activity was designed to allow the development of SRL skills and even without specific SRL support, learners appear to have been able to use the opportunity to test and develop their SRL skills. This has been reflected in the results from the SRQ-A that the robotic tutoring in the environment appears to improve SRL attitudes in general. This shows the importance of activity design for the support of developing SRL skills in a learner. However, it is not believed that the environment alone is always enough to encourage the development of SRL skills. In the earlier research in this thesis and SRL research in general it has been observed that it can be difficult for learners to engage SRL skills, so motivational support from a robotic tutor is still required to keep a learner engaged. For example in the previous research in this learning environment, if the robotic tutor does not provide motivational or domain support the learner is likely to remain in a single activity and not push themselves to learn (section 6.2) (Jones et al., 2017a).

6.3.5 Summary and conclusions

In summary, the results show that when a robotic tutor personalises and adaptively scaffolds SRL behaviour using an OLM, greater indication of SRL behaviour can be observed over the control condition, where the robotic tutor only provides domain support and no SRL scaffolding. There is some evidence of transfer of SRL skills within the activity to a different task, and also changes to the self-report of the learners' attitudes to self-regulation.

This study demonstrates how a robotic tutor can support the transfer of SRL skills by using memory and a summary of developing skills over a longer-term interaction. The effects are not necessarily short lived or due to a novelty effect. The *social robotic tutor* is effective in scaffolding SRL in a real world school environment. In the near-term transfer within the task it can be observed that the learners in the *SRL* condition were better able to cope with the introduction of the wind farm activity which asks them to use the geography and SRL skills in a slightly different and more demanding activity.

The key factors of this approach that may lead to longer-term behaviour change are using studies based in the real world school environment, using physical robotic embodiment, basing pedagogical and social behaviours on human teachers, and using behaviours that adapt to the learner to provide personalised support. Both conditions are quite close in the results of the data analysis, this may be due to the control condition still providing adaptive support, an opportunity to practice SRL skills, and motivation to the learner throughout the longer-term study. While the changes to the learners SRL behaviour are subtle these findings are encouraging as it means that the inclusion of SRL scaffolding does not detract from the interaction.

In future work the issue of the small sample size should be addressed to see if it would be possible to see statistical significance between groups. It would also be of interest to increase the duration of the study and investigate if the SRL skills could transfer to another domain.

The increased SRL skills shown in this study should help the learners to learn more effectively in the future. The approach of providing engaging, personalised support for SRL and meta-cognitive skills via a physical robotic tutor can be applied to other learning environments. These findings are important for researchers developing education technology, as supporting learners to become independent with good SRL skills is a key requirement for educators in the 21st century, as this has been observed first hand in the teacher interviews (section 3.4) (Jones et al., 2013).

6.4 Summary of the evaluation of adaptive robotic tutor

This chapter evaluates the effectiveness of the fully autonomous adaptive robotic tutor for scaffolding SRL skills in both short and longer-term studies. Study 5 (section 6.2) shows the importance of adapting the scaffolding to the individual learner's SRL behaviours to motivate the learner to engage and develop their SRL skills. Study 6 (section 6.3) shows the benefits of adaptive SRL support to improve SRL skills and attitudes as compared to adaptive domain support alone. The research has shown that by adaptively scaffolding support based on a learners SRL behaviour and performance in the activity, the learner is prompted to deploy and develop the SRL skills that teachers desire in independent learners. These findings are important for researchers developing education technology. Indeed, supporting learners to become independent with good SRL skills is a key requirement for educators in the 21st century, as had been seen first hand in the teacher interviews (section 3.4).

The benefits that personalised *social robotic tutors* can have in motivating learners in educational scenarios has also been seen. Both conditions in study 6 (section 6.3) are quite close in results regarding the perception of the robot, this is due to the control condition still providing adaptive support, an opportunity to practice SRL skills, and motivation to the learner throughout the longer-term study. The robot tutor in both conditions was well received by the learners due to its adaption to the learner and the support offered throughout the task. This is not always the case; in study 5 (section 6.2) the robotic tutor was not well received when it did not provide assistance.

CHAPTER 7

CONCLUSIONS

The thesis explores how it may be possible to scaffold SRL skills in a learner with the use of a *social robotic tutor*. This builds upon work in the ITS community on SRL scaffolding and advances in SAR research to foster people's longer-term behaviour change. A UCD approach was employed to iteratively develop a learning task, a computational model of SRL, and fully autonomous behaviours for a robot acting as a tutor. The remainder of this section will discuss the contributions, conclusions, and the lessons learnt.

7.1 Summary of contributions

Contribution 1: embodiment. The main research question was: *how could a robotic embodiment be used to support the learner to reflect on their developing skills and adopt appropriate SRL learning behaviours?* Overall, the use of an embodied *social robotic tutor* to support the presentation and explanation of an OLM had beneficial implications for trust in the OLM, motivation, engagement, learning gain, and adoption of SRL learning behaviours and attitudes.

Trust is a hot topic in the field of HRI as trust can provide the basis on which a learner improves their motivation (Saerbeck and Schut, 2010). This has implications for longer-term interaction and adoption of behaviours. In study 3 (section 3.6) having the robotic tutor highlight and explain certain aspects of the OLM could lead to an increase in trust of the model compared to the condition where no robot was present. The adaptive or personalised formative feedback offered by the robotic tutor needs to be trusted by the learner so that they are motivated to use the feedback. The combined use of social robotic embodiment and OLM on-screen for personalisation leads to a higher perception of trust to motivate and engage the learners to demonstrate SRL processes.

In study 4 (section 3.7) the teacher balances formative feedback with motivational feedback to ensure that the learner is motivated and focused on the task, whilst not feeling under pressure. If the feedback is not adaptive then it may not be appropriate to the learner and they will not be able to make use of it and may become frustrated and demotivated. When similar autonomous behaviours were implemented in a robotic tutor in study 5 (section 6.2), in addition to increasing learning gains, embodied social adaptive feedback was also able to reduce some of the anxiety or tension associated with the use of an OLM. This mirrors other research which showed that feedback of a more social nature leads to better performance (Kollöffel and Jong, 2015). However, social factors alone are not enough to lead to learning gain; a robot could be designed so that it is well perceived by a learner but this may not challenge or motivate the learner to engage in the activity or SRL processes. Study 6 (section 6.3) shows that when a learner receives personalised timely formative feedback that they trust, this can lead to longer-term behaviour or attitude changes. *Contribution 2* discusses how to model the students' SRL skills as a basis to adapt and personalise SRL scaffolding.

Another benefit of a physical embodiment, is that the robot can exhibit shared attention with the user and show contingent behaviours, i.e. the robot is able to gaze where the user interacts with the activity. This can form the basis of a relationship of syncronicity or joint attention, which may help to synchronise the learner's goals with those of the robotic tutor. A learner may perceive a closer relationship with a robot that is able to display accurate contingent or empathic behaviours (Cramer et al., 2010). Indeed, in this research when the robot has been able to adapt to the learner and provide support, the robot is perceived well.

This is the first research project that has used a robot to scaffold access to an OLM. It is firmly believed that the effects that have been seen could not be achieved with more traditional on-screen feedback or prompts, as these prompts would distract from the activity. The physical embodiment overcomes the issues with all reflection based scaffolding of prompting the learner to reflect without breaking the flow state of learning as the prompts can be given in a much more natural and subtle way.

Contribution 2: computational model of SRL scaffolding. A model of SRL has been developed for the learning scenario which allows adaptation based on a learner's domain knowledge and SRL skills. The following research questions were addressed: *Can a robot computationally detect and model reflection and SRL skills of a learner in real time? Can this computational model be used to improve the personalisation and adaptability of a robotic tutor?* In study 4 (section 3.7) teachers were observed using an OLM to scaffold SRL skills. These observations were contextualised within the relevant theory in section 5.1, and guidelines identified for SRL scaffolding based upon an OLM. In section 5.2 a strategy is described that should be employed when the learner deviates from an ideal SRL model.

The support offered by the robot does not only facilitate reflection by highlighting the OLM, it also provides domain, motivation, planning, and goal orientation support to prompt the learner to engage SRL skills. In previous research only one or two aspects of SRL are addressed (Kitsantas, 2013). In this research it is argued that SRL is affected by both the learning context and social factors. This approach is required as the best tutors are concerned simultaneously with a learner's learning on one hand and their motivation on the other: this ensures that the student is involved in and persists with the learning task (Du Boulay and Luckin, 2016).

The approach is also based on the principles of socio-constructivist theory where the learner's development is supported by social interaction. The learners development is also supported in the Vygotsky's Zone of Proximal Development (ZPD) approach where the social robot can adjust the difficulty of the task either directly or by offering support, so that the task is at an appropriate level for the learner. The social robot aims to move from providing external regulation of SRL skills, through co-regulation, and finally to allow the learner to fully self-regulate their own learning. This is achieved by adapting the scaffolding to the learners' domain knowledge, mastery of the activity and their adherence to the model of SRL. Other research shows that the degree to which learners actively engage in self-regulation is influenced by the tutor's behaviour and the environment (Urdan and Turner, 2005; Kitsantas, 2013).

The aim is to achieve a longer-term behaviour change toward greater SRL skills. This approach also prevents the learner from becoming overly focused on outcome goals which may be encouraged by having skill meters present. The robotic tutor and OLM can be used as a basis for goal setting and encourage the learner to employ more appropriate SRL behaviours once an activity is mastered. The learner is also supported and encouraged to use more forethought and to be intrinsically motivated by using summaries of previous sessions and wrap-ups, which the teachers demonstrating in study 4 (section 3.7).

The computational model of SRL is built on observations of experienced human tutors and merging this with theory. The computational model of SRL and the personalised behaviours developed are of use in this style of learning scenario and for this age group of children only.

Contribution 3: evaluation methods and metrics for SRL in short and longer-term interactions. A potential road map for other researchers to follow when evaluating the scaffolding of SRL skills has been proposed. This was motivated by the following question: *does the personalised SRL scaffolding delivered by a* *robotic tutor impact learners' perception of the robot, activity, motivation, SRL skills and learning gain?* In section 6.1 the measures and metrics for learners' perception of the robot, activity, motivation, SRL skills, and learning gain are described which could be used by other researchers in the future. In section 4.2 the development of a learning scenario that allows the learner the freedom to use and develop their SRL skills is described. Both study 5 (section 6.2) and study 6 (section 6.3) show how the metrics and measures apply to the learning scenario. In the future these measures and metrics could be used to further personalise support to individual learning differences. Study 5 (section 6.2) explores how to evaluate different levels of personalisation. Study 6 (section 6.3) shows how to evaluate differences over multiple sessions when comparing different types of scaffolding. Both short and longer-term studies have been conducted to explore how an adaptive and personalised robotic tutor may support SRL skills. Ideally, running a study over a greater duration than a month and exploring further opportunities to observe if SRL skills transfer to other domains, or persist without the robotic tutors presence would also be worthwhile. However, as learners' reactions change over time each child has to be given sufficient time and opportunity to adjust to the presence and unfamiliar nature of the robot, which creates considerable time constraints. Indeed, it must be noted that longer-term studies are still rare in the literature and it follows that the longer-term evaluation over a month with the same children is a significant accomplishment.

The high level measures and analysis that were performed should also be applicable to other studies of SRL or other studies with *social robotic tutors*. The lower level specific measures for the learning scenario would be best used as guidelines for the types of metrics that are available in other learning scenarios.

Contribution 4: iterative UCD approach. This research shows that a UCD approach can be used to develop and evaluate a *social robotic tutor* that takes into account the needs of the teachers and learners. The key aspects of a successful UCD approach are:

- Including teachers and learners where possible at a very early design stage is essential to create a system that the teachers would welcome in their classroom and fit into their curriculum. Feedback provided here led to the development of the learning scenario as a whole including the learning aims, the learning task, the role of the robot, and the contents and interaction with the OLM.

- Running studies in the users' environment is very important as running studies in a lab setting may cause the users to react in a very different way. To address this issue students were made familiar with the robot and all of these studies were performed in the participants' schools.

- Prototypes can be very useful. The learning task was prototyped and developed through study 2 (section 3.5), study 3 (section 3.6), and study 4 (section 3.7). These prototypes have enabled the development an environment that is suitable for the final evaluations.

- Observing human teachers in study 2 (section 3.5) and study 4 (section 3.7) has been very beneficial to understanding theory within this context and implementing practical models and behaviours used in the final system. This is very beneficial as it can be difficult for teachers to explain in detail how they would adjust to different students' needs on the basis of an abstract description of the task. It should be noted that other works in the area of robots acting as educational agents have primarily been built upon results of previous studies from educational psychology, rather than following a UCD approach (see section 2.2). This is a novel contribution of this research.

7.2 Limitations

7.2.1 Limitations of UCD approach

The main limitation of the UCD approach followed in this research is that it requires a lot of time from the end users, which can be difficult to obtain. There are also a number of issues surrounding the recording of such an amount of rich data on children. At times, there was a trade off in terms of placing the study inside a school and also being able to video and record the study. There can also be considerable set-up times involved. It would certainly be much easier to perform the studies in a lab at the university.

7.2.2 Limitations of the learner model

It would have been interesting to be able to build more sophisticated learner and pedagogical models that took in to account individual learner's preferences and learning styles, potentially using machine learning techniques. However, this would have required gathering substantially more data which was limited due to the restricted availability of teachers, learners, and number of robotic tutors. With more data it may be possible to be able to have the robot learn behaviours from teachers' behaviours and past interactions with learners. It may also be possible to have a robotic tutor learn the learner's preferences in real time using reinforcement learning techniques (Chi et al., 2010).

It would also be interesting to investigate how learners with different learning styles or personality types would react to the scaffolding. This could be achieved by asking the Big Five Questionnaire-Children (BFQ-C) (Barbaranelli et al., 2003).

7.2.3 Sensing abilities of the robotic tutor system

Teachers in section 3.4 reported that they detect difficulties with a student through a variety of means, including: a visible confused facial expression, the learner asking for help, and lack of progress or incorrect actions in the task. The system developed was able to detect difficulty through lack of progress and incorrect actions in the task, unfortunately the robotic tutoring system was limited in the visible and subtle sensing abilities. Human teachers are able to make sense of the learner's affect, their gaze, body posture, general disposition, and many other factors to more effectively support the learner. In relation to SRL behaviours, learners were observed reading out loud to focus attention or thinking out loud while solving problems, these behaviours would be good indicators of SRL processes and could be encouraged by the robotic tutor if they could be sensed.

7.2.4 Interaction abilities of the robotic tutor

A human teacher is able to engage in a dialogue with a learner to better understand the difficulties that the learner is facing. The learner is also able to query the teacher asking for specific assistance. In the design of the learning interaction a help button was not added due to a fear that the learner may use such a button to game the system or have the robot perform an action for entertainment (Aleven et al., 2006). In some cases the learner might question the assessment of the system and the reason for the OLM giving a particular value, this is an opportunity for a negotiable learner model (Kerly, 2009).

7.2.5 Duration of interactions and sample sizes

As with many HRI studies there was a trade off between interaction duration and sample size due to the availability of the robot and that the interaction needed to be supervised in case there were issues. The interaction time in the studies with the robotic tutor presented in section 3.6 and section 6.2 were shorter to enable a greater number of participants. The longer-term study presented in section 6.3 was of a greater duration over the sessions at the expense of the number of participants. Studies of a longer duration would enable there to be a baseline gathered of a learners SRL skills before SRL support is given. It would also provide an opportunity to observe transfer of SRL skills some time after SRL support is removed.

To support the longer duration studies there would also need to be more domain material so that learner would have material to work on. There would also need to be further work on the interaction abilities of the robotic tutor to ensure that it would be able to maintain the interaction with a learner over this time, endowing the robotic tutor with the ability to wrap-up and provide a summary as presented in this research, is a step in this direction.

7.2.6 Limited demographic

All of the learners that took part in the studies were from schools in the Midlands in the UK and of a similar age range. Learners from other locations and backgrounds may respond differently to the robotic tutor and its tutoring style.

Age range

The learning task and SRL support was designed to support the 10 to 12 year old age range of children and their typical level of development of SRL skills. The support offered would be too advanced for younger children and may lead to them becoming frustrated. The support offered is potentially too simplistic for older children and may lead to them becoming disengaged.

7.2.7 Application to other domains

The support offered by the robotic tutor was loosely coupled to the learning task domain. However it does require a learning task with a number of activities and tools for the learner to choose from. It would be possible to create a similar open-ended learning task and domain model for other domains which would be useful to test the transfer of SRL skills from this domain to another.

7.2.8 Reliability of coding

The data collection, transcription, and coding for the studies presented in section 3.4, section 3.5, and section 3.7 were performed by the author of this thesis. It would be desirable to have multiple researchers transcribing and coding audio and video to check the quality of the coding scheme with inter-coder reliability checks.

7.2.9 Comparison to virtual agent

One final potential limitation is that the research did not seek to compare virtual to physical embodiment. However, arguably it has been sufficiently shown that a physical embodiment is generally more advantageous than a virtual embodiment (Leyzberg et al., 2012).

7.3 Future work

This research did not seek to compare the robotic tutor to a human tutor; there is no doubt that a human tutor would be the most effective, given their greater experience and perceptive abilities. Rather, this research explores the unique capabilities of a robotic tutor, these benefits include motivation, patience, and consistency. It is hoped that in the future as the cost of robotics decreases, teachers will be able to use robotic tutors to support their lessons and introduce new learning activities, by providing students with motivating, personalised, and longer-term SRL tutoring, with the added benefit of effectively freeing up teachers' time.

Based on the promise of the approach of using a robotic tutor to scaffold SRL skills found in this research and the limitations described above there are a number of avenues of investigation to pursue.

7.3.1 Greater interaction with robotic tutor

Much of the areas of future work are dependant on greater sensing and interaction abilities of the system in general.

Adapting to the learners' affect, engagement, cognitive development needs, and individual preferences

The pedagogical and learner models developed in this research appeared to work well. They supported adaption based on a learner's SRL indicators, knowledge, skill levels, and task performance. As the learner's showed more SRL behaviours and ability in the task the support offered by the robotic tutor was reduced.

The SRL scaffolding offered by the robotic tutor aimed to support the learner's affect through motivation statements. However, it did this without any true understanding of a learners affect. Understanding and adapting to a learner's affect is of growing interest e.g. the EMOTE project[1]. Despite it being a difficult task, there is growing interest in detecting and responding to affective states, e.g. (Calvo and D'Mello, 2010; Woolf et al., 2010; Zhang, 2012; Ramachandran and Scassellati, 2015; Jones et al., 2015d; Leite, 2013). A taxonomy of "academic emotions, which are directly related to academic learning, classroom instruction or achievement", has been identified (Pekrun et al., 2002): the positive activating emotions of enjoyment, hope, and pride; the positive deactivating emotion of relief; the negative activating emotions of anger, anxiety, shame; and the negative deactivating emotions of hope-

[1]http://emote-project.eu/

lessness and boredom. A key part of SRL is the ability for a learner to self-regulate their emotions and place themselves in positive emotional states such as enjoyment, hope, and pride. With a greater knowledge of the learners affect the SRL scaffolding could be used to support the learners with this aspect of SRL. Opening up a system's representations of a learner's affective state in an OLM could further influence learner affect (Girard, 2011).

Personalising the interaction based on a learner's engagement can be beneficial to learning (Szafir and Mutlu, 2012). There is work underway to measure and adapt to engagement using cameras, microphones, and Kinect sensors (Ramachandran and Scassellati, 2014; Deshmukh et al., 2015a).

The learner model presented here was updated based on evidence of task performance, however greater accuracy of learners' knowledge may be gauged with Bayesian active learning (Gordon and Breazeal, 2015). This would be able to support more fine grained support.

The rules for the scaffolding offered by the robotic tutor were hand crafted and may not apply equally well across all learners. One approach to explore would be reinforcement learning (Martin and Arroyo, 2004; Chi et al., 2011) where the system to adapts to individual learners preferences. The system would take into account the results of any support/intervention to better tailor the support to the learner in the future. This type of approach would require longer duration studies to collect the detail necessary to create the learner model and pedagogical models to support this approach.

Negotiation of learner model

It could be possible to build upon the OLM and support offered by the robotic tutor to allow the learner to discuss or even negotiate values in the OLM. The process of negotiating the learner model can cause learners to become more engaged, reflect more, and help the learner develop better self-assessment skills (Kerly, 2009).

Memory

The robotic tutor is able to utilise the learner model as a memory of the learners' development in the current and previous interactions. This enables the robotic tutor to provide summaries of the learners' development through the current session, in the form of a wrap-up at the end of the session and the learners' development over all previous sessions in the form of a summary at the beginning of a session. The wrap-up and summary map support the learners' reflection and also help to build and maintain a good social interaction (Leite et al., 2013). One area of investigation would be to explore and develop this feature with some more focused studies comparing different types of memory and summaries. For example, by endowing the robotic tutor with an autobiographic memory may lead to more appealing and human-like engaging interactions (Dias et al., 2007).

7.3.2 Expansion of the learning task

The learning task developed in this research had more than enough material to keep the learners occupied. Even without specific SRL support, learners appear to have been able to use the opportunity to test and develop their SRL skills. This has been reflected in the results from the SRQ-A that the robotic tutoring in this environment appears to improve SRL attitudes in general.

However, further research would benefit from adding more activities to support longer-term interactions and to support SRL in slightly different contexts. Particularly activities along the lines of the wind farm activity which requires problem solving skills, use of tools, and making decisions and trade offs.

7.3.3 Transfer of SRL skills to other domains

The expansion of the learning task could also be used to investigate the longer-term adoption of SRL skills so that they are adopted as a general behaviour. It would also be beneficial to add other domains to the learning task, which might allow investigation of the transfer of SRL skills from one domain to another. By adding more material it would be possible to use longer-term studies to further explore longer-term behaviour change. This is a key target of HRI and ITS research (Tapus et al., 2007; Begum et al., 2016; Koedinger et al., 2009). To investigate this longer-term behaviour change it may not require a vastly different system to the one described in this research, just the time and resources to run the studies.

7.3.4 Exploration with virtual agents

One of the limiting factors in running studies of a longer duration or with more participants is the lack of availability of robotic tutors. The use of virtual agents instead of a robotic embodiment would enable studies to be longer in duration and to be run in parallel. It has been shown that a physical embodiment is preferred to a virtual embodiment (Leyzberg et al., 2012; Jones et al., 2014b). However, SRL scaffolding can still be effective with a virtual agent (Wagster et al., 2007b; Koedinger et al., 2009). One avenue of research would be to compare the robotic embodiment to a virtual embodiment. If the virtual agent is successful then larger scale studies could be investigated.

7.3.5 Comparison to a teachable agent

In this research there was a conscious decision to explore scaffolding from a robotic tutor. This enabled the robotic tutors behaviours to be based on observations of teachers behaviours and scaffolding strategies. However, there is increasing amount of research that shows the benefits of teachable agents both in the areas of ITS and HRI (Hood et al., 2015; Tanaka and Ghosh, 2011; Charisi et al., 2015; Wagster et al., 2007b). It would be interesting to explore how a learner could develop and practice SRL skills by teaching a teachable agent to use and develop SRL skills.

7.4 Concluding remarks

In summary, this research has demonstrated that a social robot can engage and motivate a learner to use SRL processes in a learning scenario. The OLM helps to counteract some of the limitations in the interaction modalities of a robotic tutor, e.g. the length of time it takes to deliver feedback by speech. Conversely, a robotic tutor can make up for some of the limitations of an OLM whereby feedback can be given in a more subtle or natural way without breaking the flow of the interaction. Using a model of SRL allowed the robot to adapt the SRL scaffolding to a learner, this allows the robot to move effectively from external regulation of SRL skills, to co-regulation of SRL skills, and finally through to the learner being able to use SRL skills with no support at all.

CHAPTER 8

APPENDICES

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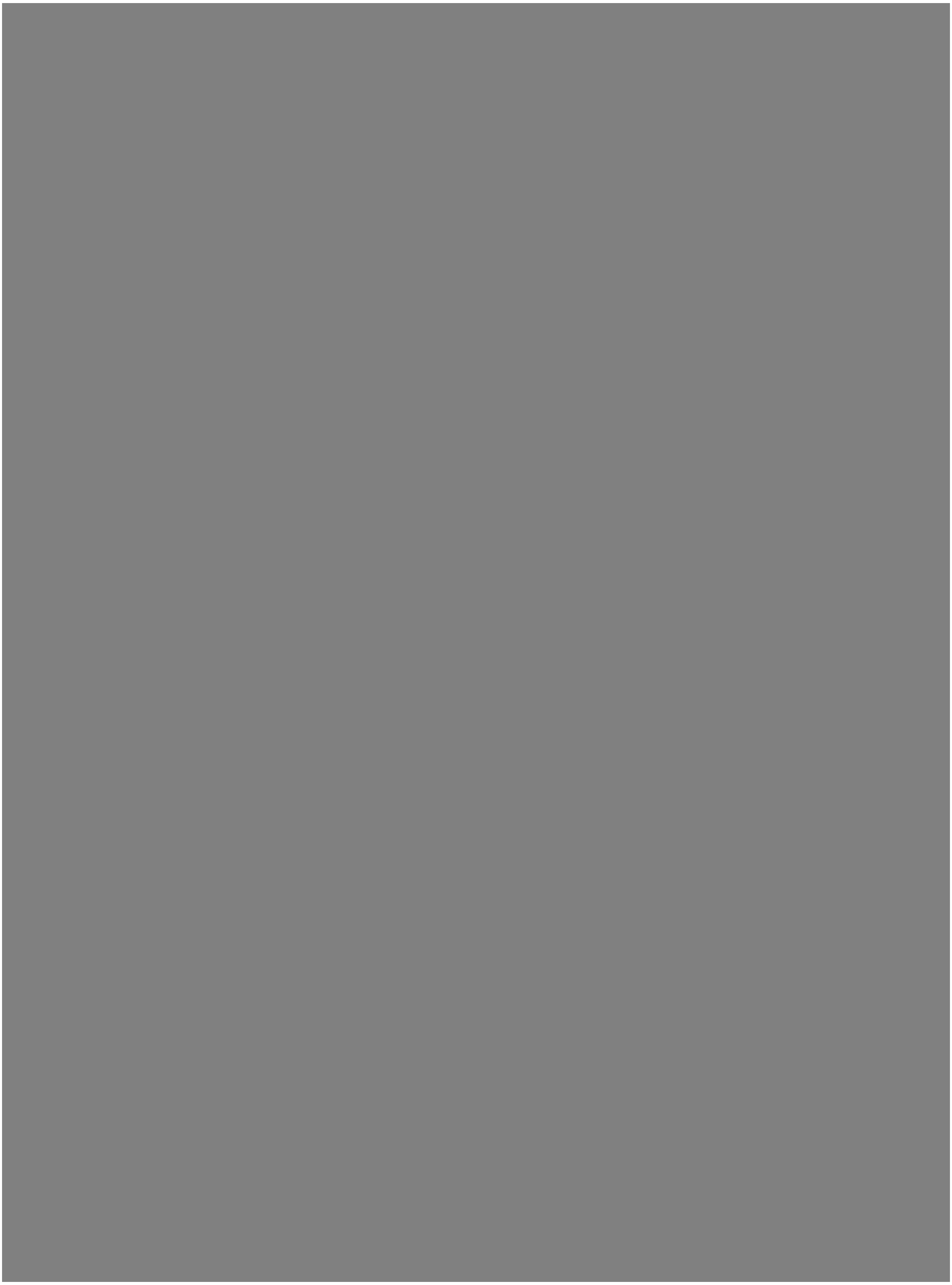
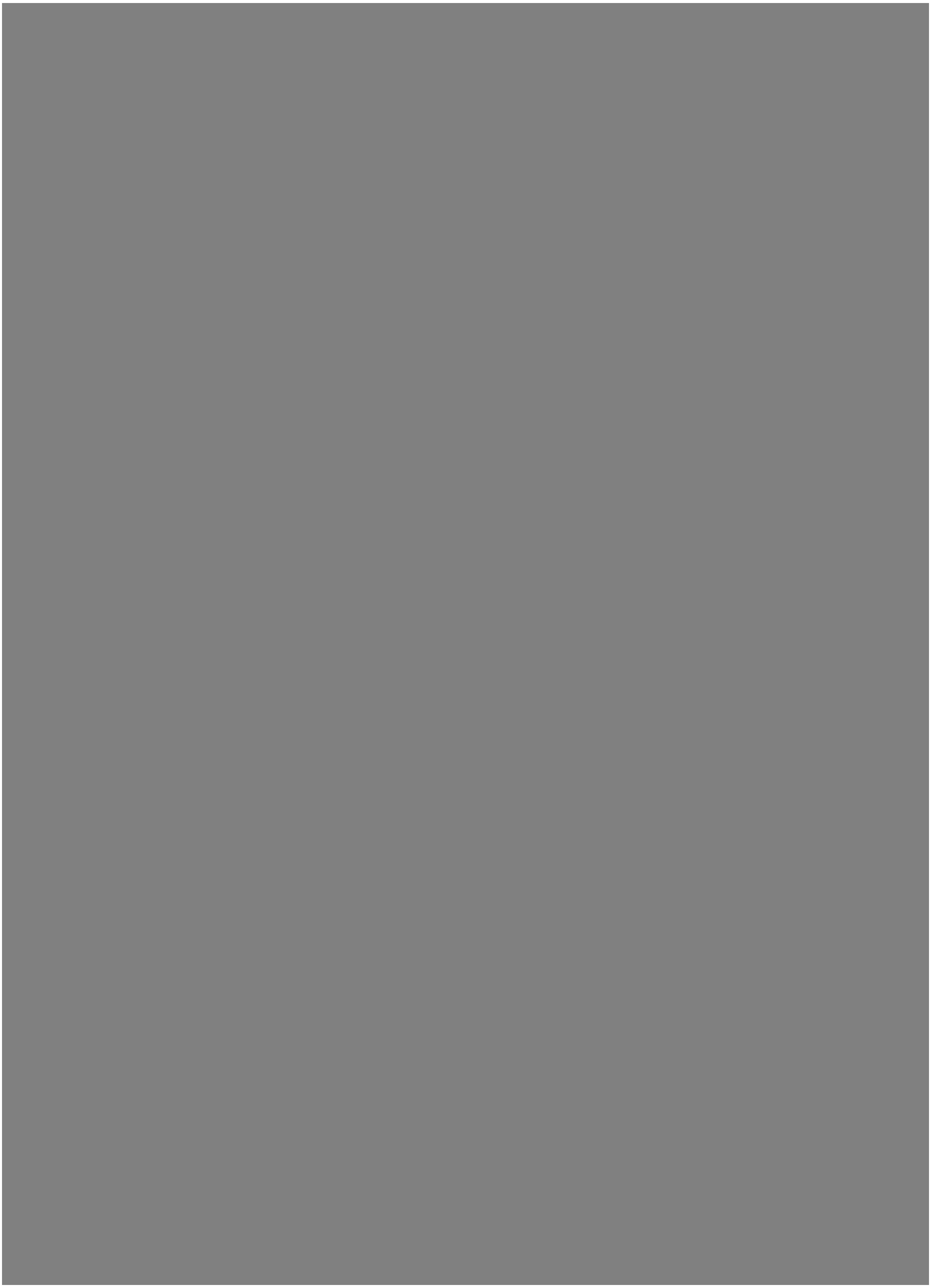
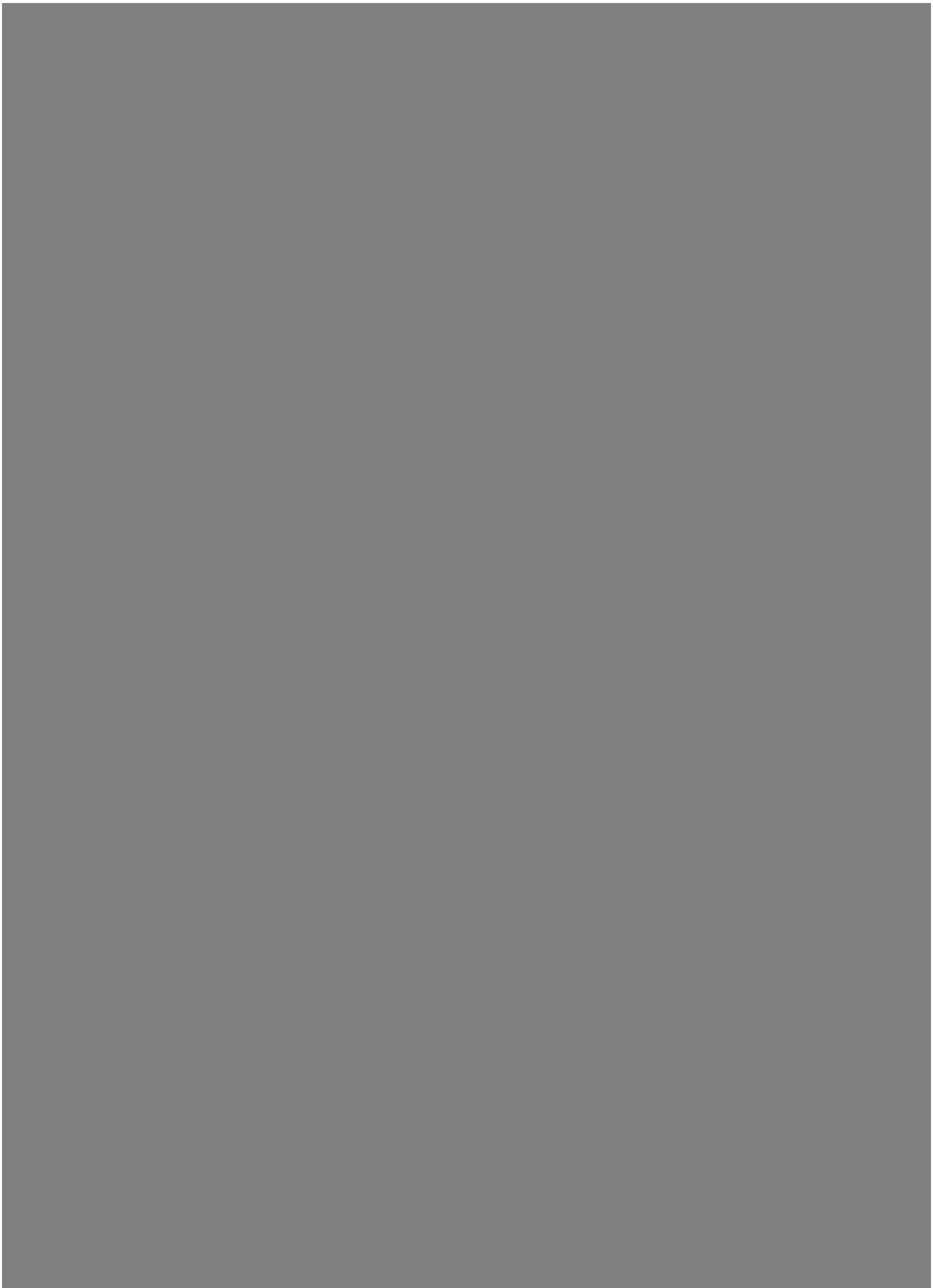
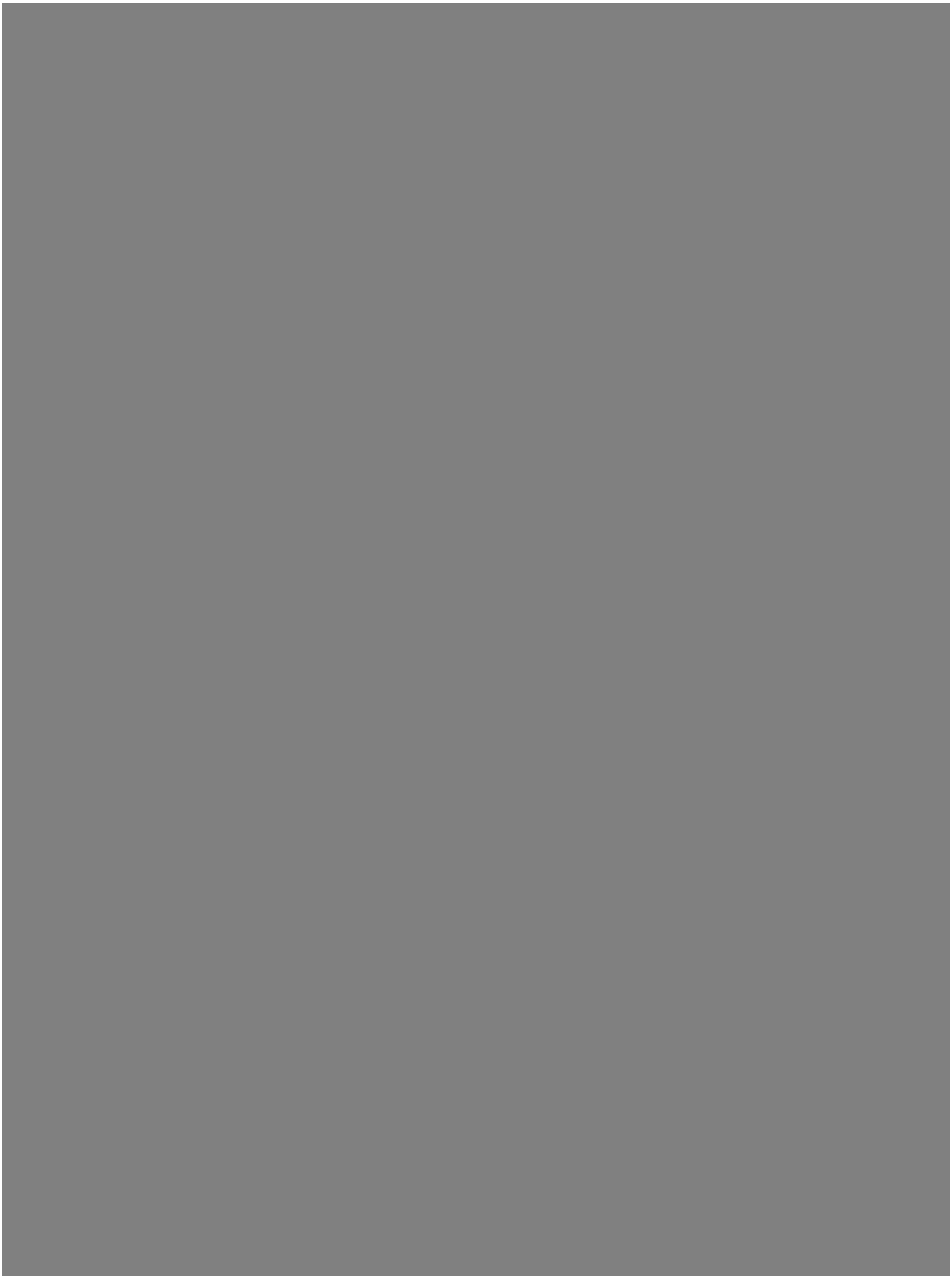
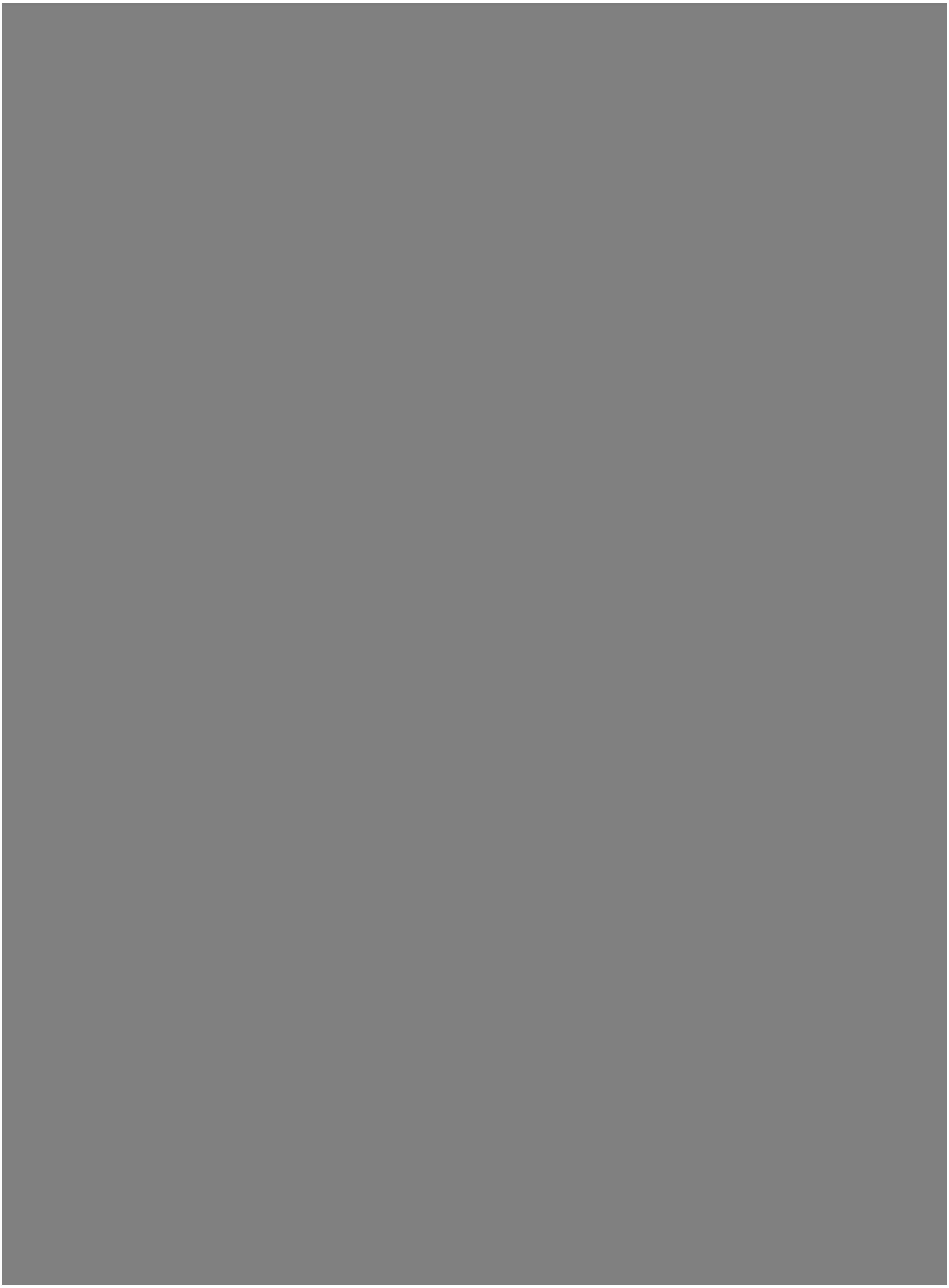
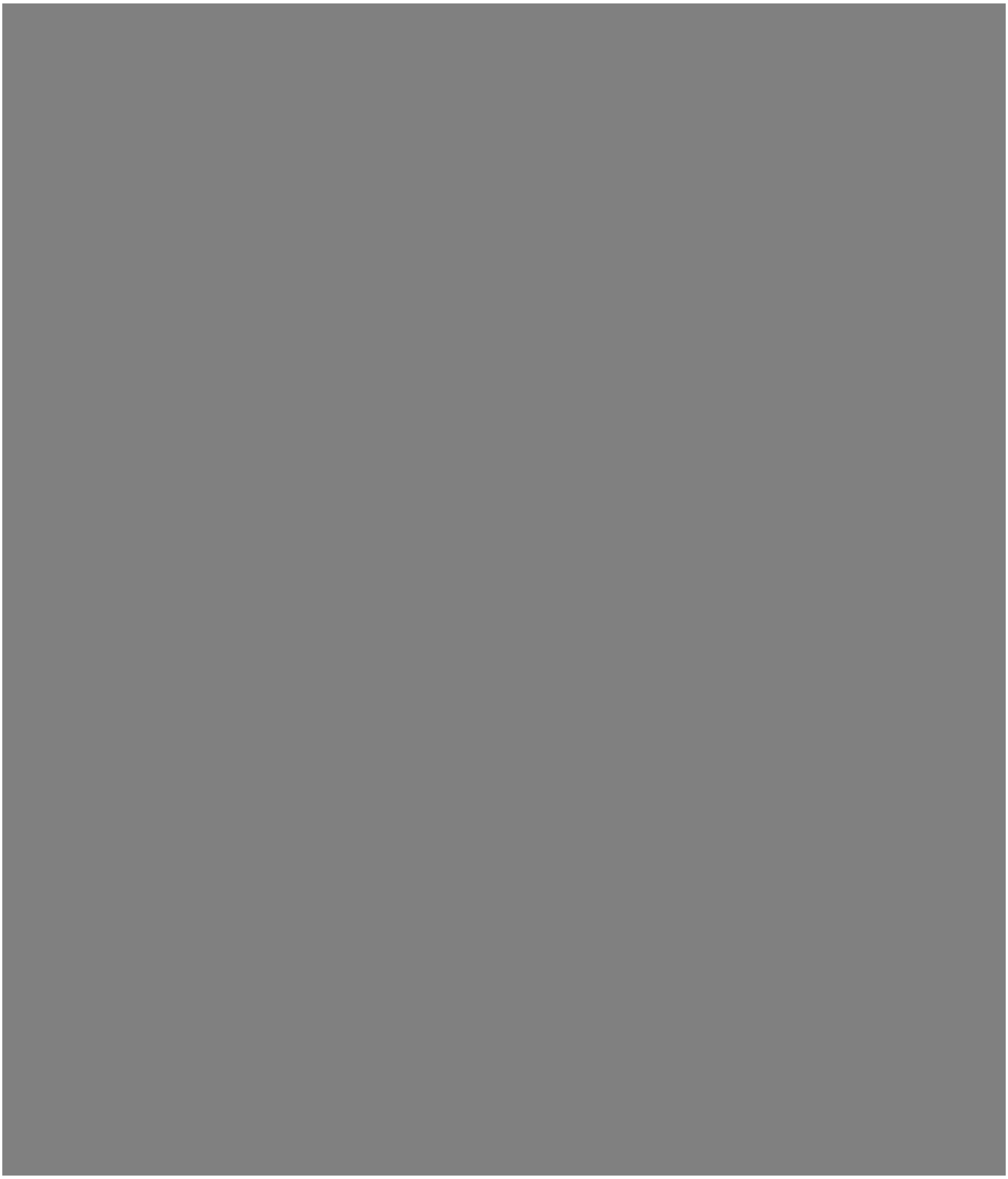












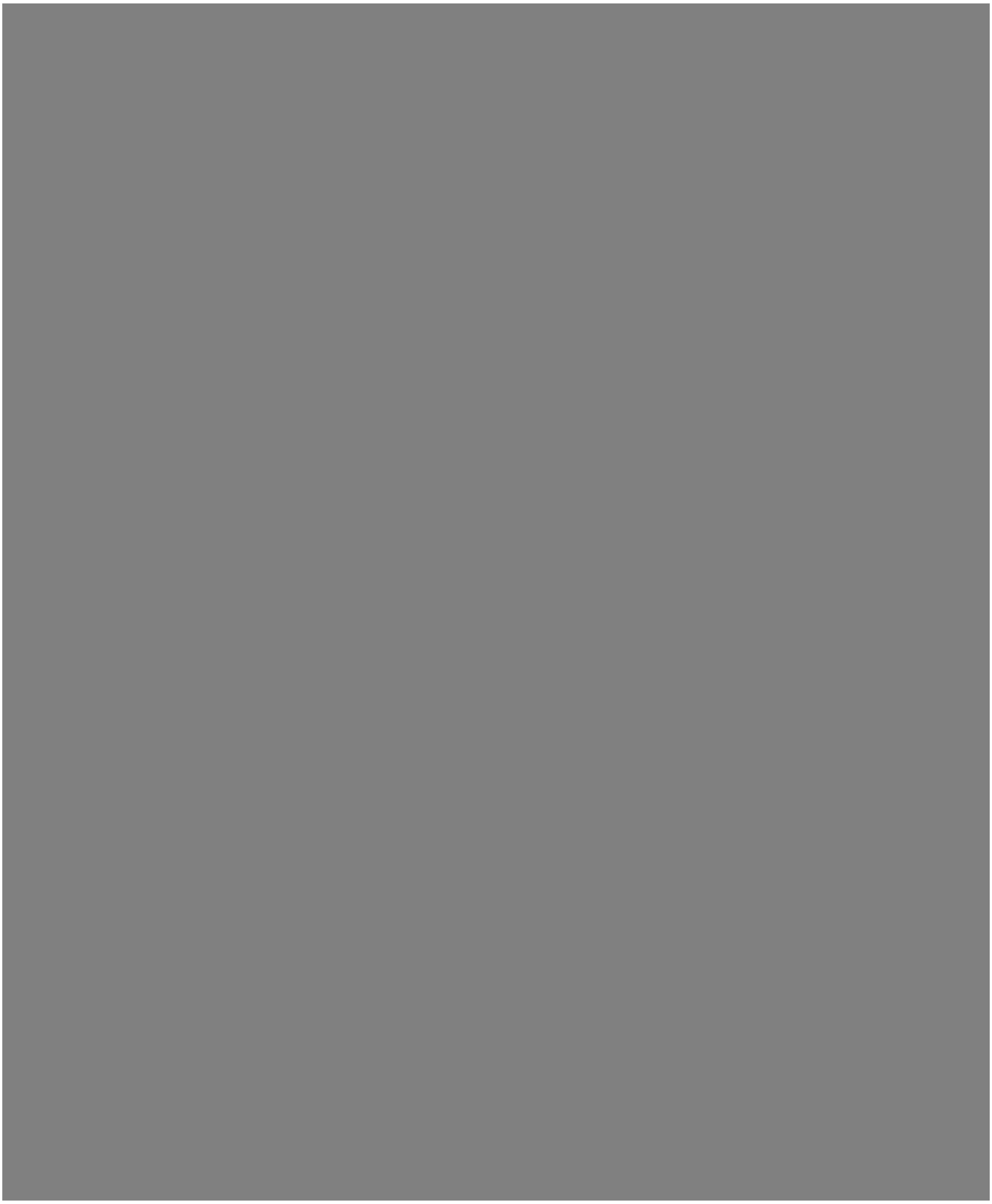
8.2 Questions used in study 1: teacher interviews

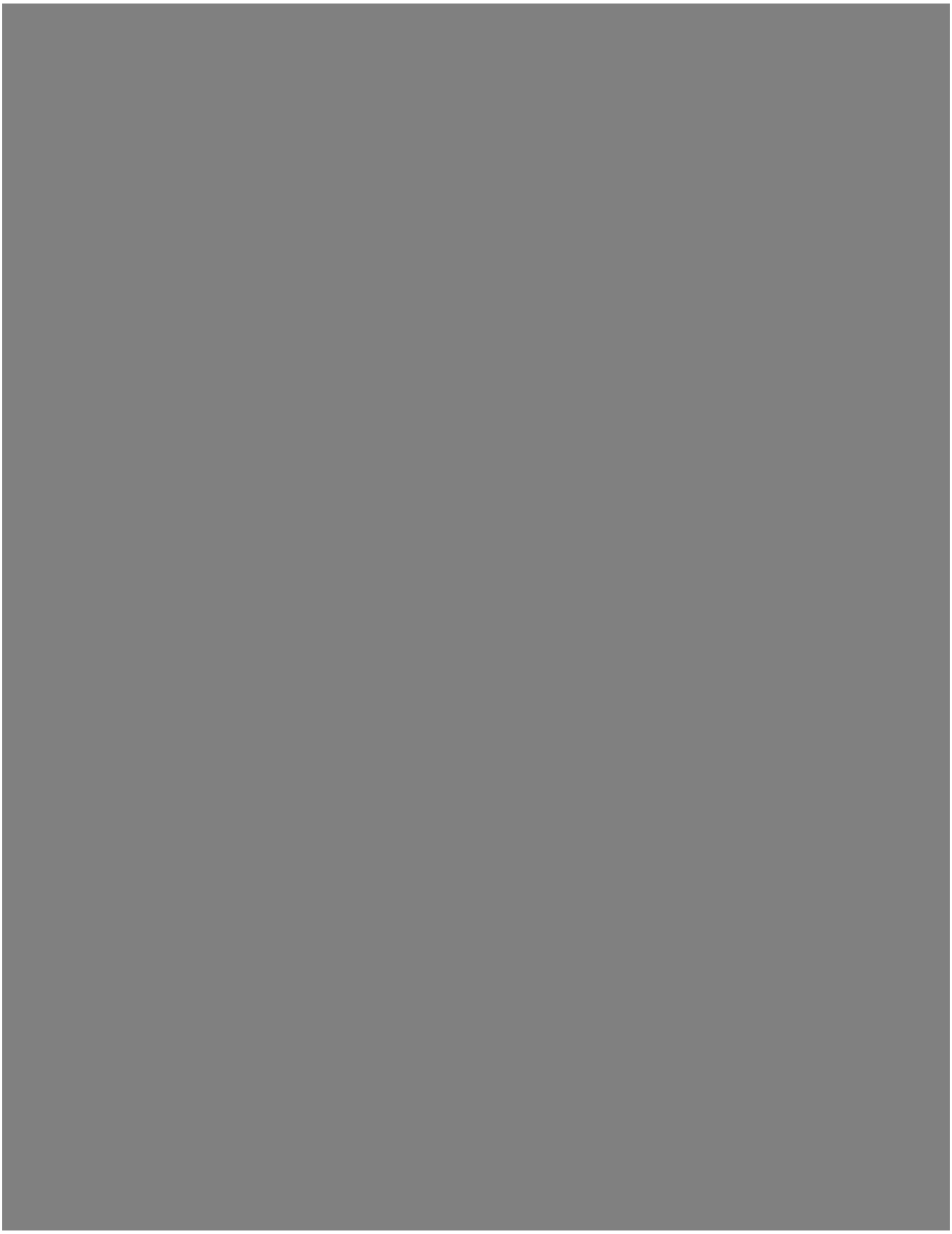
The following questions are the full set of questions used in section 3.4.

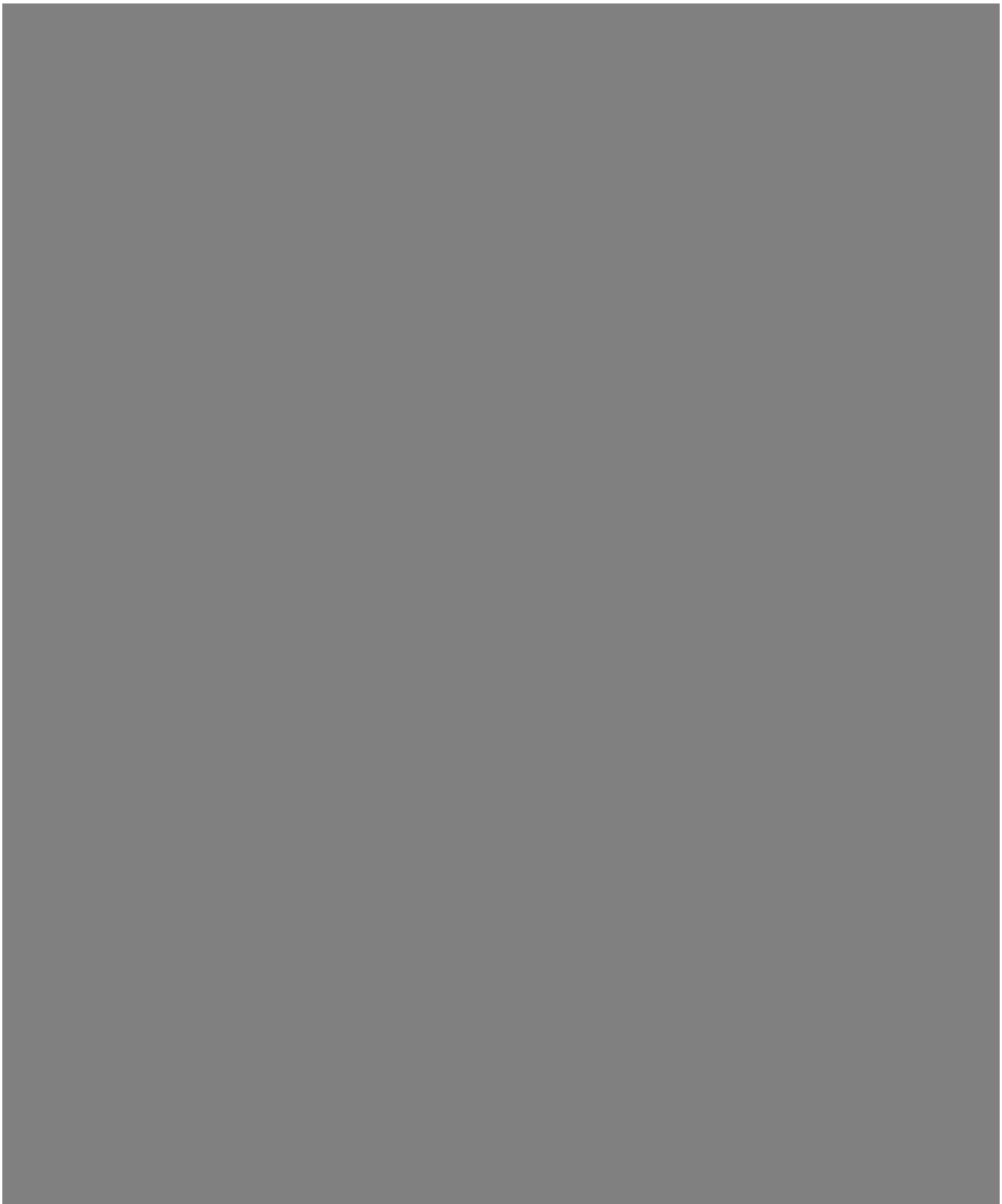
- How plausible is it to have such a robot and touchscreen table set-up in lessons?
- Ideally how many pupils would interact at any one time? What would other pupils be doing?
- What role would a system like this play?
- Anything similar in place with more individual exercises, e.g. with a learning assistant?
- If you had a robot that could monitor how well a child is completing an activity how would you like that robot to interact with the child?
- Would it be beneficial to set the level of difficulty (e.g. difficult, medium, easy)? How do you set difficulty at the moment?
- How do you detect when a student is having difficulties and how do you help the learner overcome the difficulties?
- Has the school investigated or have in place other technology enhanced learning activities e.g. iPads
- Any concerns with having such a system in the classroom?
- How could we plan our content/scenario in order to allow for multiple interactions with the same child

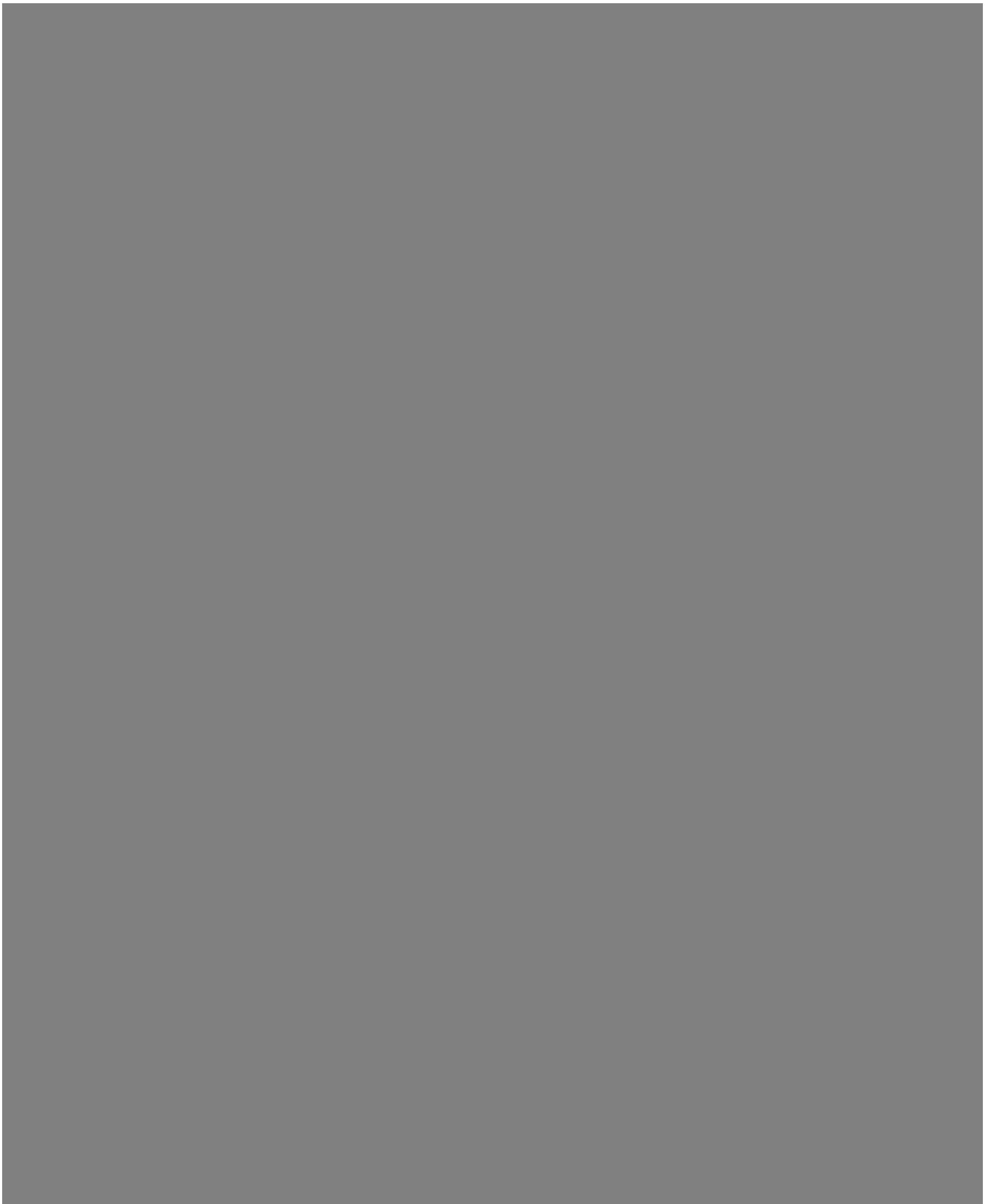
8.3 Activity used in study 2: mock-up study

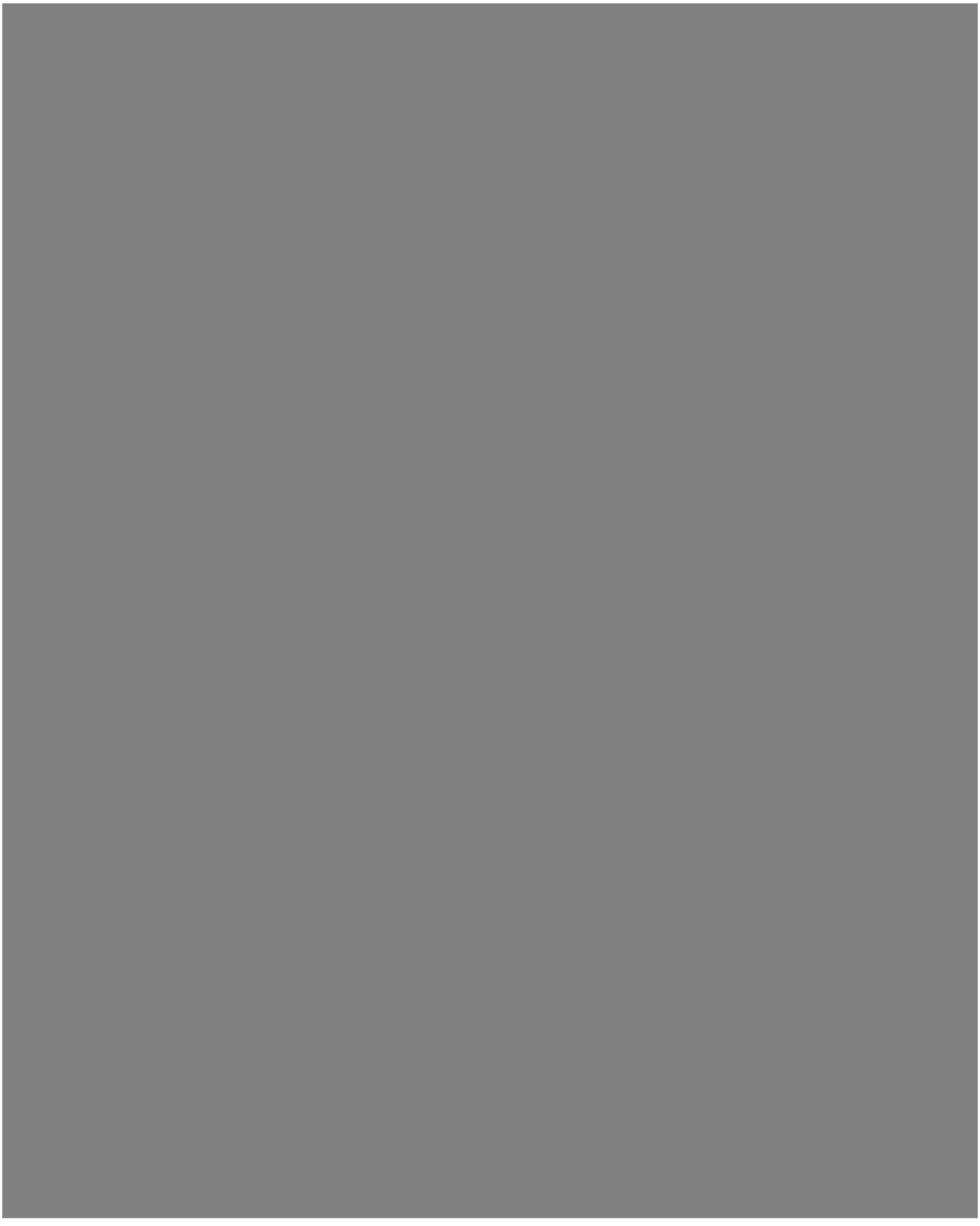
This is the full paper based activity that was used in section 3.5. The activity was based on requirements gathered in section 3.4 and also a review of existing activities











used in the curriculum e.g. Digimap for Schools[1].

Title of activity:

Map Skills and Building Activity

Level:

11 - 13 years old

Context:

Reading maps

Location:

Local

Knowledge /skills:

Reading and following directions on maps. Considerations when placing a new building based on map reading skills.

Note to teacher:

The amount of independent work children are able to manage will depend on their familiarity and experience of using maps in general. The step by step tasks are not meant to be read alone by children but as a guide for you the teacher to demonstrate or direct individuals as appropriate. The contexts for the learning include both 'physical' and 'human' geography, and will explore different scales of mapping.

[1] http://digimapforschools.edina.ac.uk/

Activity

Pupils use given clues to follow direction on a map, they will follow a route. The pupil will then be asked to place the building in one of the locations.

Introduction Trails are fun for children and help them to read and use maps with greater confidence. We provide maps at a range of scales and the large scale maps are very detailed. This helps pupils to get better at recognising map features as they learn how to take virtual 'walks' through the landscape. What is most important is that that they recognise that these coordinates give detailed information about where something is. They can learn to use maps in an relaxed and fun way. This activity can be done in class but it links very well with fieldwork in the locality where pupils can research and plan their own trail and this makes an ideal follow up activity.

Resources

- Map of local area.
- Compass points on a transparency.

Main activity There is a trail mission. Read the clues and follow the trail on the map. Finally using the skills you have learnt you will choose the location to place the wind farm.

Tasks

- Read your trail mission and find the start location.
- Read the next clues carefully and find your trail on the map.

- When you have found the end of the trail, show on the map where you think you should place the new building and note the Grid Reference.
- Your teacher will know if you are successful or not.

Trail clues: wind farm trail QT–1 is a Robot that will be joining the class soon. We are going to follow the trail so that we can learn the skills to choose the location to build a new wind farm to power QT–1. Can you follow the trail and build the wind farm?

Clues

1. The start of the trail is at Haybridge High School can you find this on the 1:2500 scale map?
2. Can you follow the Brake Lane East until you reach a crossroads?
3. What are the names of the roads at the crossroads?
4. Which Building is at the North East corner of the crossroads?
5. Can you see the Playing Field on the map? Which direction is this from the Church?
6. Which direction is the school from the Playing Field?
7. How many meters is it between the Schools Sports Hall and the Church?
8. How many meters is it between the Church and the centre of the Playing Field?
9. How many meters is it between the Playing Field and the School?
10. Can you find the School on the 1:10000 scale map?

11. What do you think the blue symbol of a man is for? You can look at the OS Explorer Map Key to find out.

12. How many Public Houses are there on the map?

13. How far is the Stourbridge Golf Club from the School? Hint the Golf club is North of the School.

14. Can you see a forest with only Coniferous Trees?

15. Can you see a forest with only Non-Coniferous Trees?

16. Can you see a forest with a mixture of Coniferous and Non-Coniferous Trees?

17. Can you see road less than 4m Wide?

18. Can you see a secondary road?

19. Can you see a main road?

20. Can you point to the public telephone nearest to the School?

21. How high is the School?

22. Where is the highest point on the map? It is towards the East of the School. (309m East of the map near The Four Stones.)

23. Can you see Wychbury Hill it is East North East of the School?

24. How High is Wychbury Hill?

25. Can you see Palmer's Hill it is West South West of the School?

26. How High is Palmer's Hill?

27. The closer the contour lines are together the steeper the hill, Which is the steepest hill between Wychbury Hill and Palmer's Hill?

28. Can you find the School on the 1:20000 scale map?
29. The roads look different on this scale map. Can you point to a secondary road?
30. Can you point to a main road?
31. Can you point to a primary Route?
32. Can you point to a motorway?
33. The school is in Grid reference 89 80.
34. On this map can you place the wind farm? Place to the south. It needs to be above 130 m in height. It cannot be near a nature reserve.
35. It needs to be face south west to get the best wind can you point it in that direction?
36. What is the grid reference for this position?

8.4 Questions used in study 3: embodied OLM study

The following questions are the full set of questions used in section 3.6.

8.4.1 Questionnaire – pre-activity

This was the questionnaire given before the activity. The students were also asked their name and age.

Demographics:

All questions are on a five point scale ranging from “Strongly Agree” to “Strongly Disagree”.

1. I have experience with computers
2. I have experience with robots
3. I have experience with touchscreens

Skill level:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I am good at distance measuring
2. I am good at compass directions
3. I am good at reading map symbols

8.4.2 Questionnaire – post-activity

This was the questionnaire given after the activity.

Skill level:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I am good at distance measuring
2. I am good at compass directions
3. I am good at reading map symbols

Enjoyment/engagement:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I enjoyed the overall experience
2. I enjoyed doing the activity
3. I enjoyed being shown my skill levels throughout the activity
4. I enjoyed the explanation of how and why my skills changed
5. I lost track of time while doing the activity
6. I would like to play the activity again

Perception:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I noticed that the system understood my skill levels
2. I noticed that the system showed me my skill levels
3. I noticed that the system explained why my skill levels were changing

Understanding:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I understood when the system showed me my skill levels
2. I understood the explanation of why my skill levels were changing

Utility:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. Having the system show my skill levels helped me identify my strengths
2. Having the system show my skill levels helped me identify areas of difficulty
3. Having the system explain why my skill levels were changing helped me identify my strengths
4. Having the system explain why my skill levels were changing helped me identify areas of difficulty

Trust:

All questions are on a five point scale ranging from "Strongly Agree" to "Strongly Disagree".

1. I trust that the system can gauge my skill levels correctly
2. I trust that the skill levels shown by the system were accurate
3. I trust the explanation of why my skill levels were changing

Open questions:

1. What did you like about the feedback the system gave you?
2. What did you dislike about the feedback the system gave you?
3. Is there anything you didn't understand about the system, exercise or feedback?
4. What are the main differences between being helped by the system and being helped by a teacher or teaching assistant?
5. What are the main advantages of being helped by the system rather than by a teacher or teaching assistant?

6. What are the main disadvantages of being helped by the system rather than by a teacher or teaching assistant?

7. How would you improve the system?

8.5 Task and robot questionnaire used in study 5 and 6

These questionnaires are described in section 6.1 and are used in both section 6.2 and section 6.3.

8.5.1 Questionnaires about the learner

Demographic questionnaire

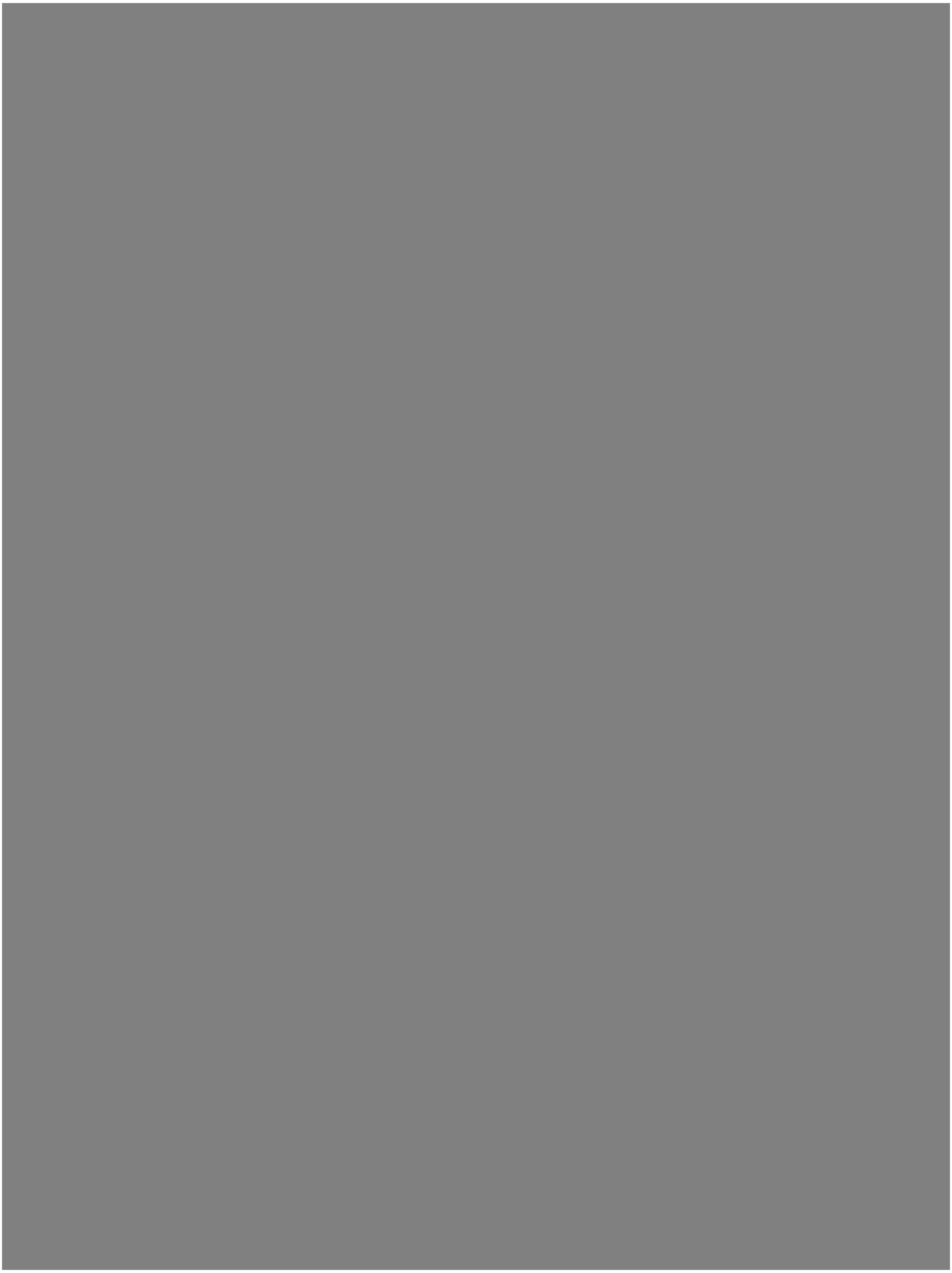
These demographic details were recorded in each study.

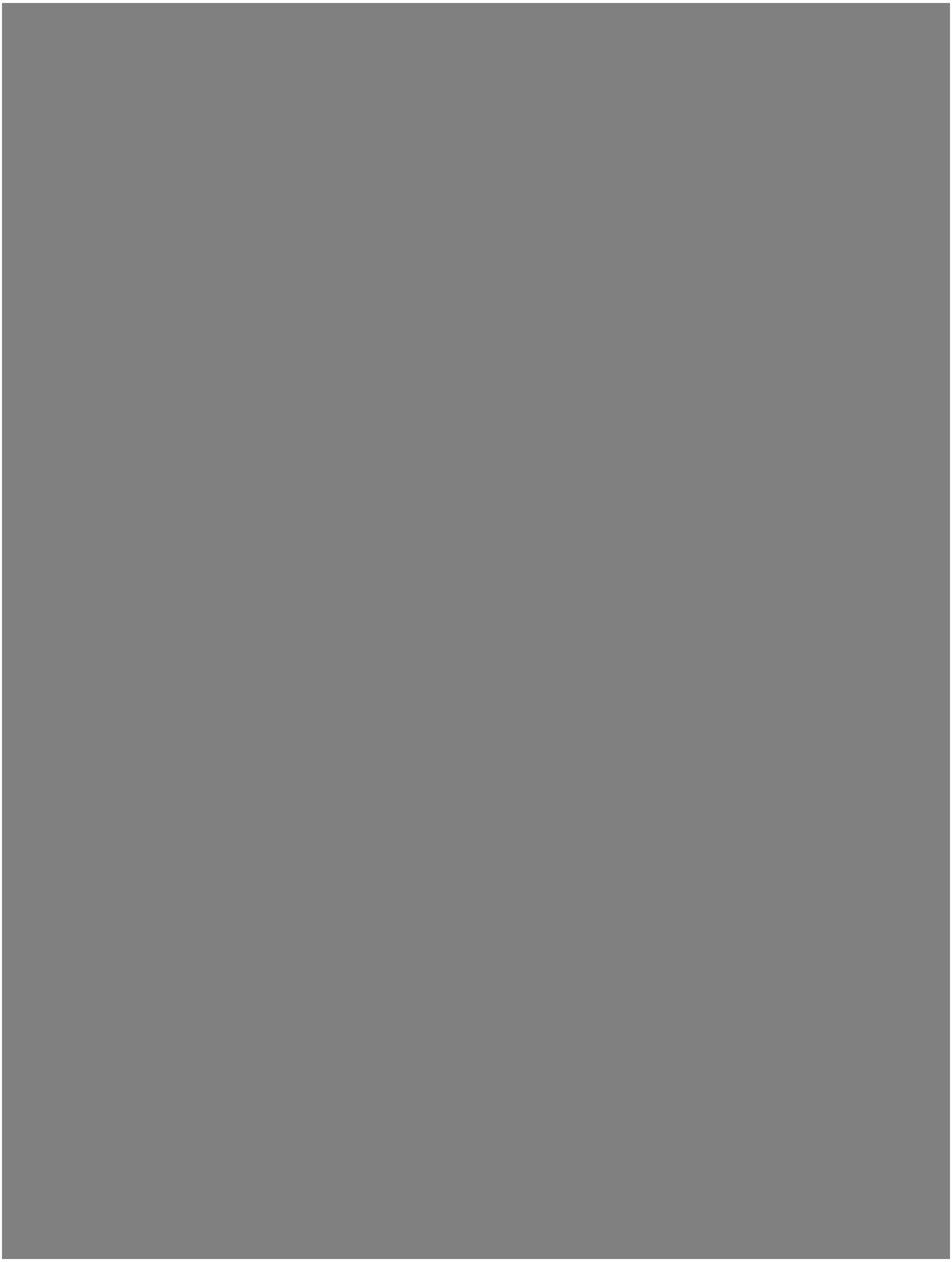
- "My sex is" M or F.
- "My age is" 9,10,11,12,13,or 14.

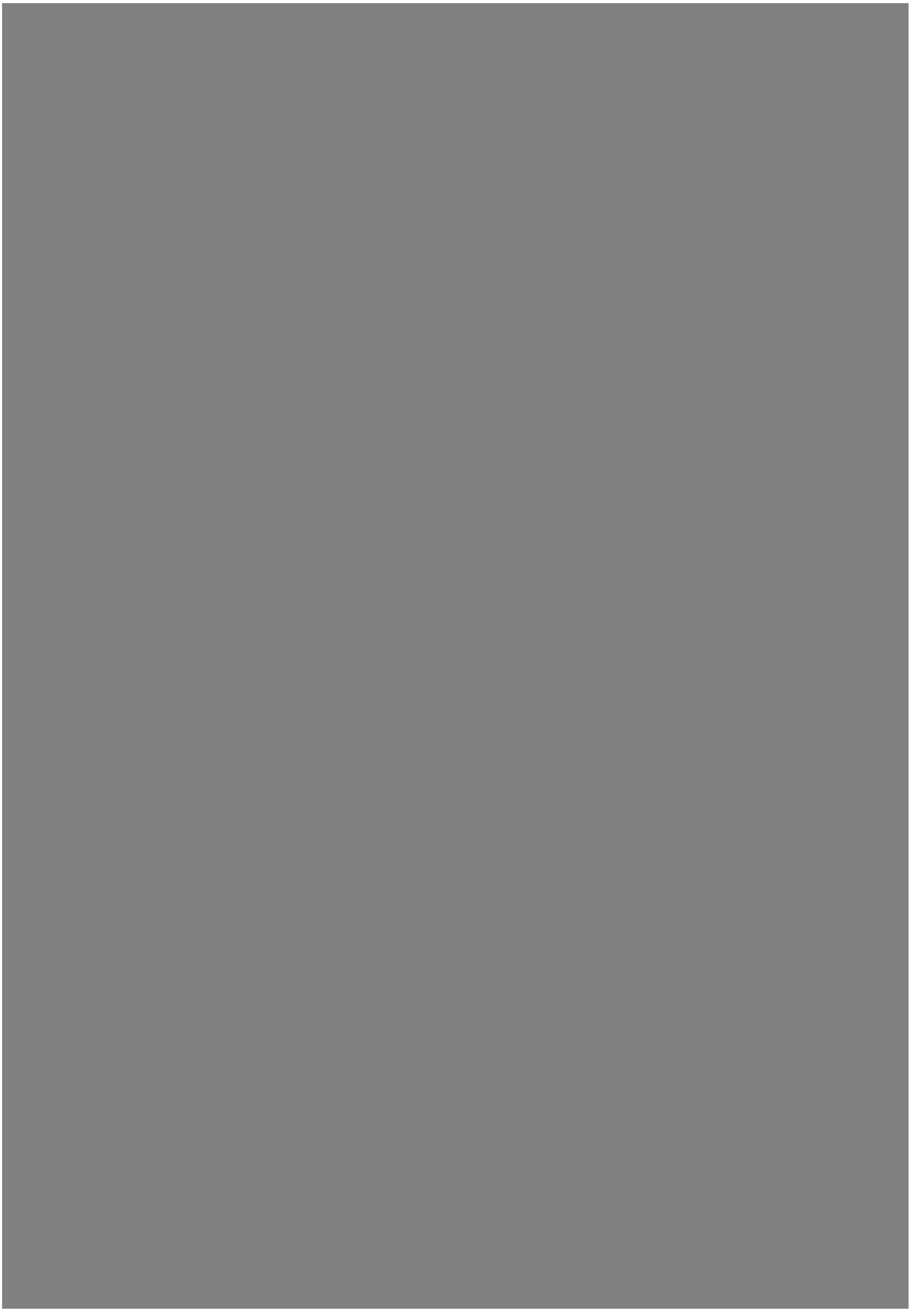
Domain skill self-assessment questionnaire

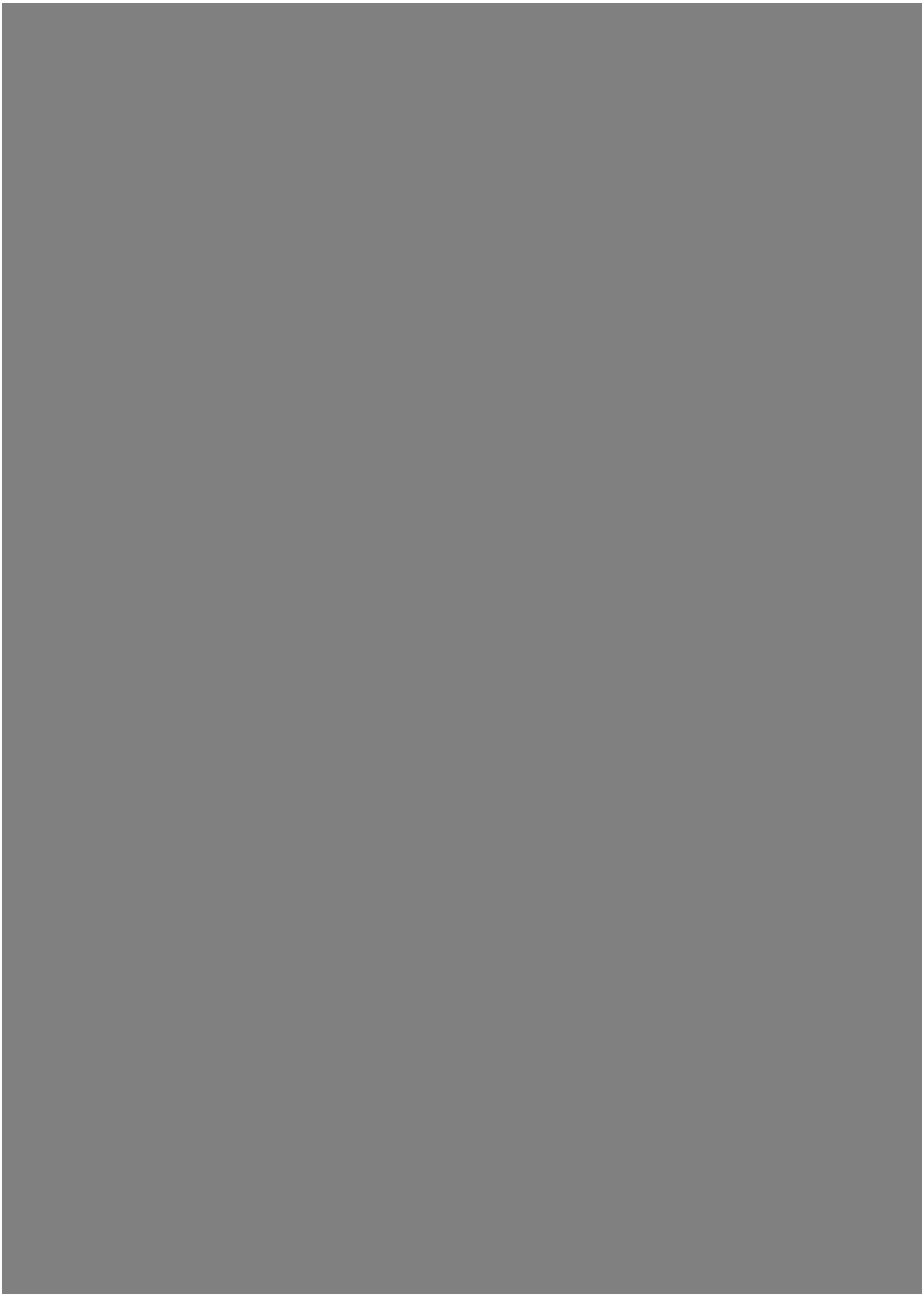
This was used as a pre-test and post-test in various studies. These competency/skill based questions are asked on a 5 point scale of "Very Low","Low","Okay","Good","Very Good".

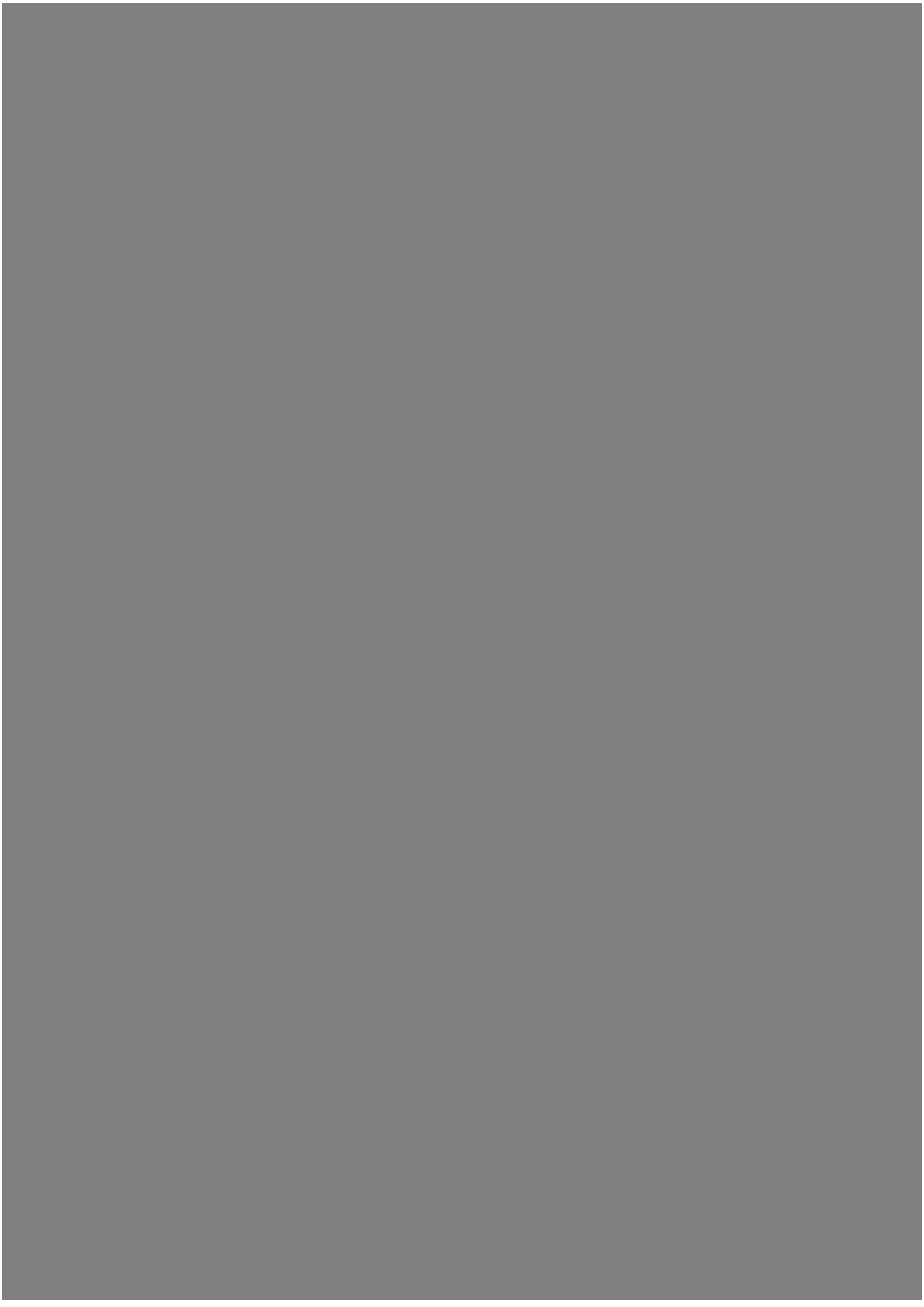
- "My skill at distance measuring is"
- "My skill at compass direction is"
- "My skill at map symbol reading is"

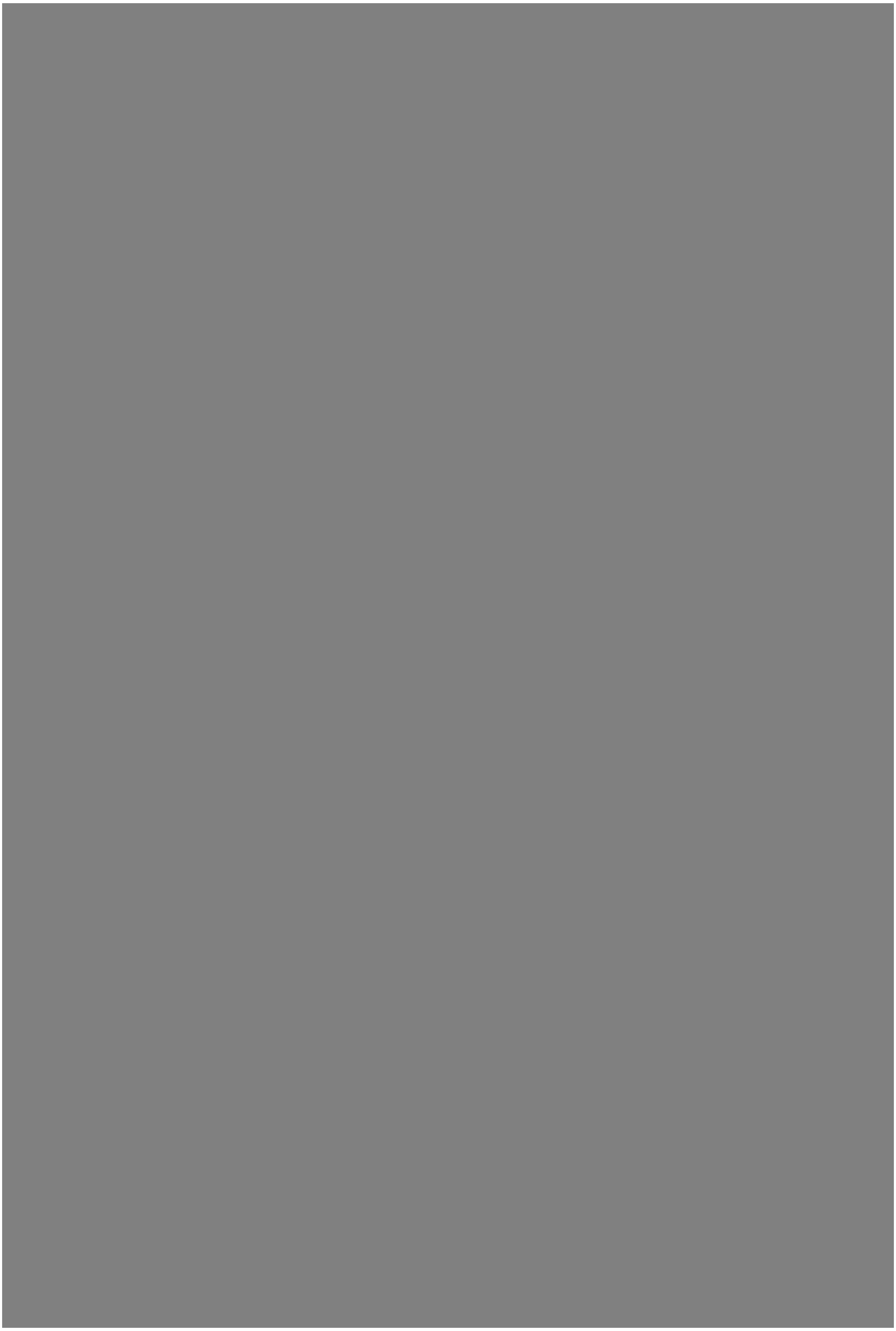


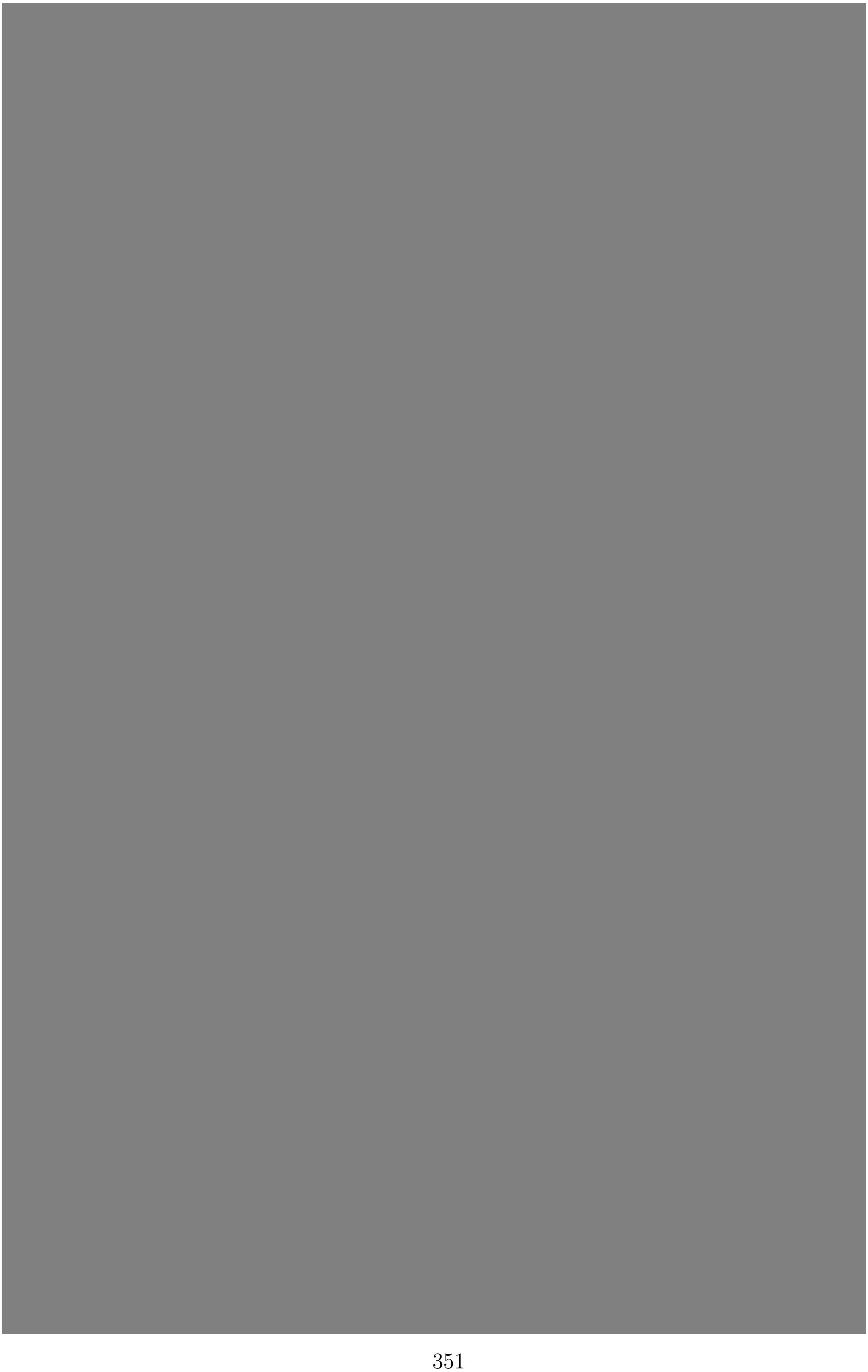


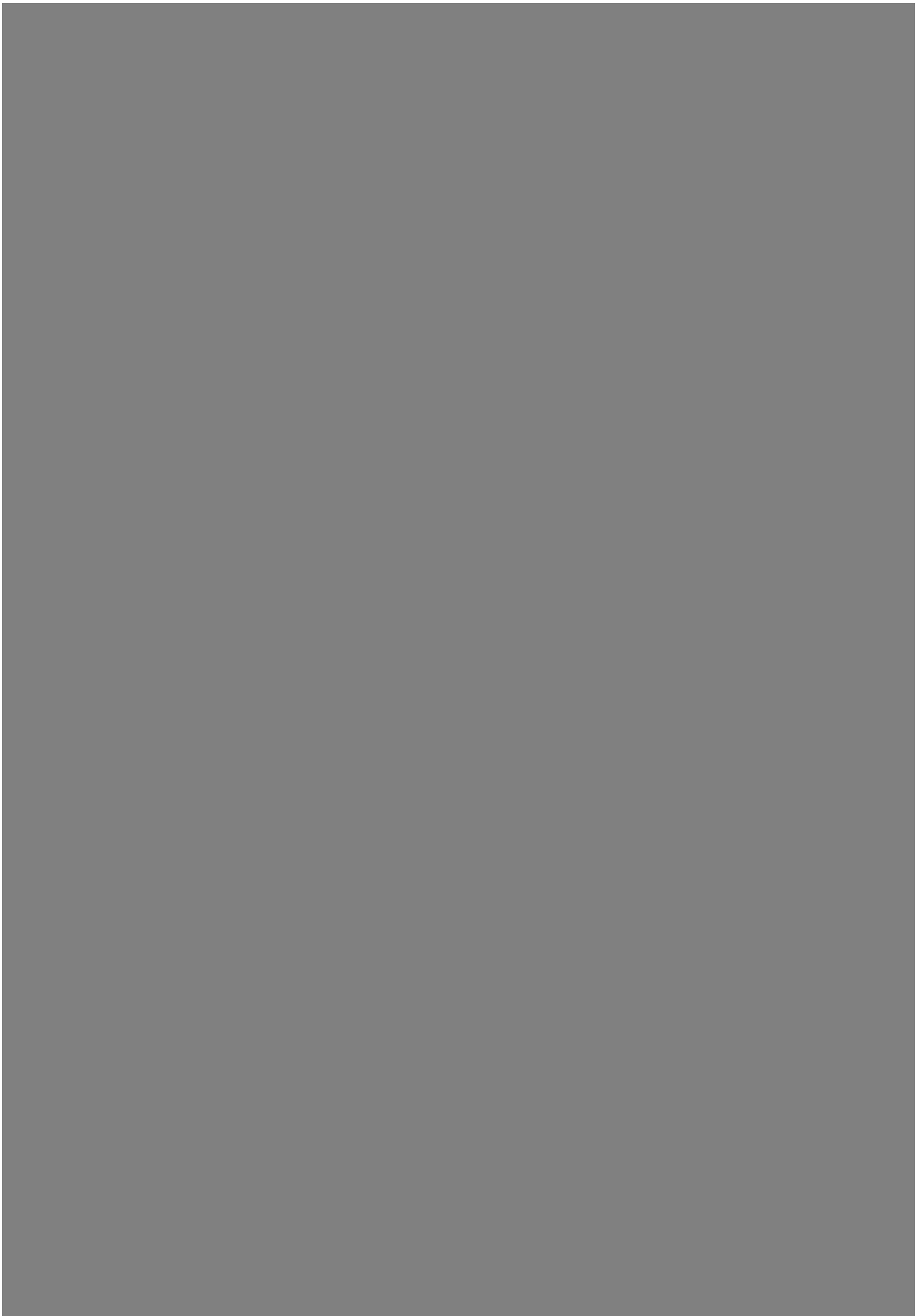


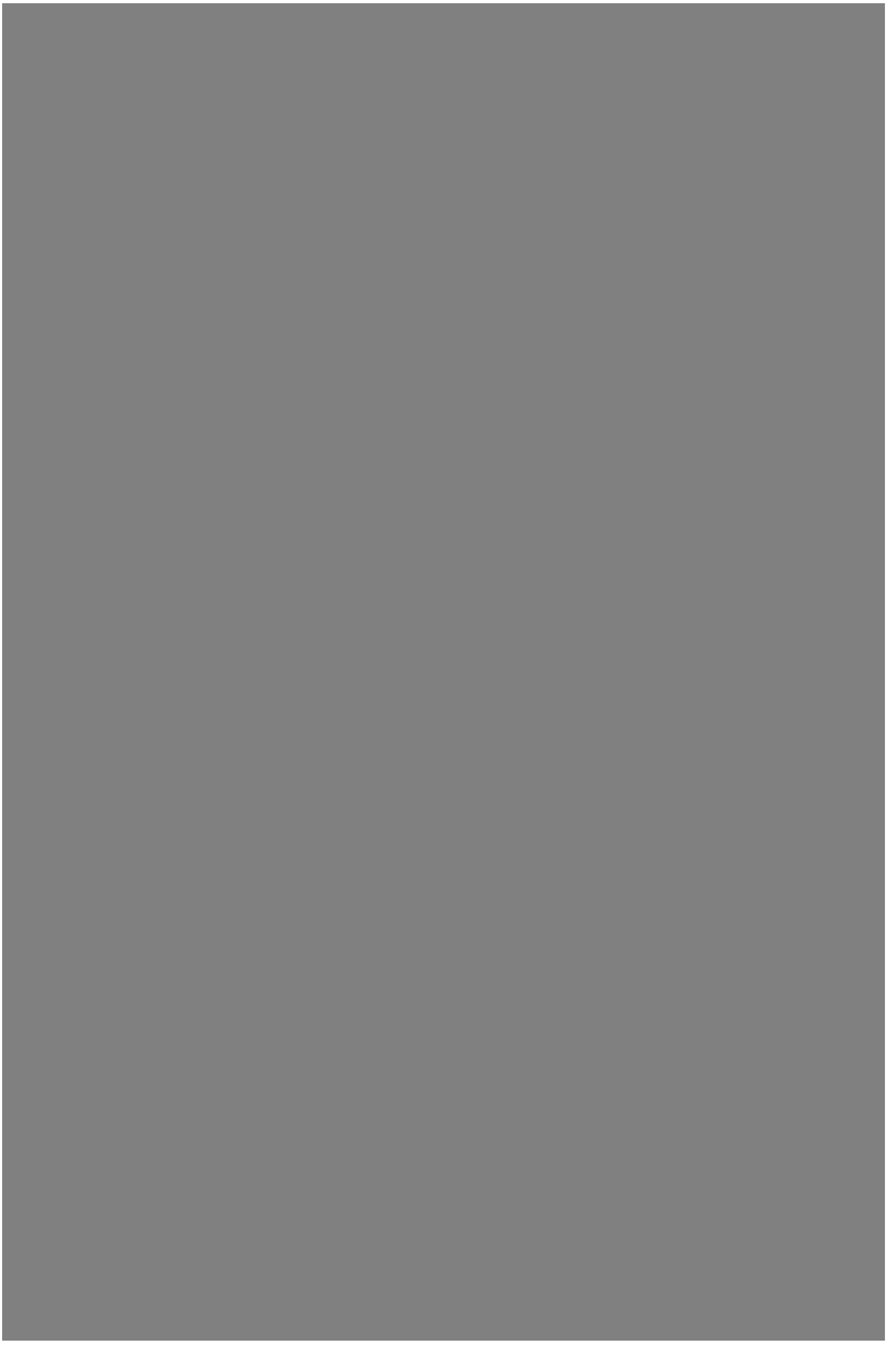


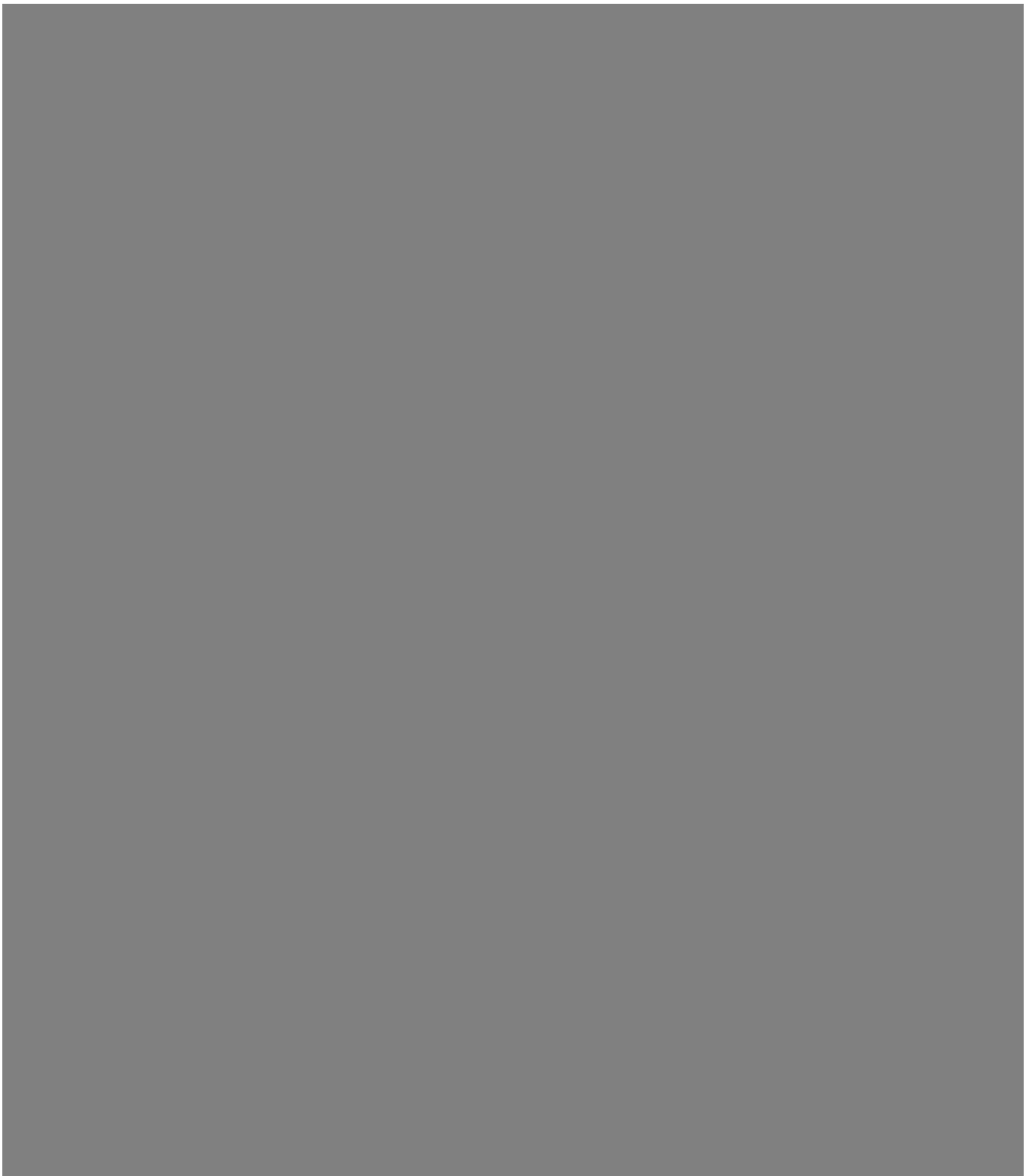


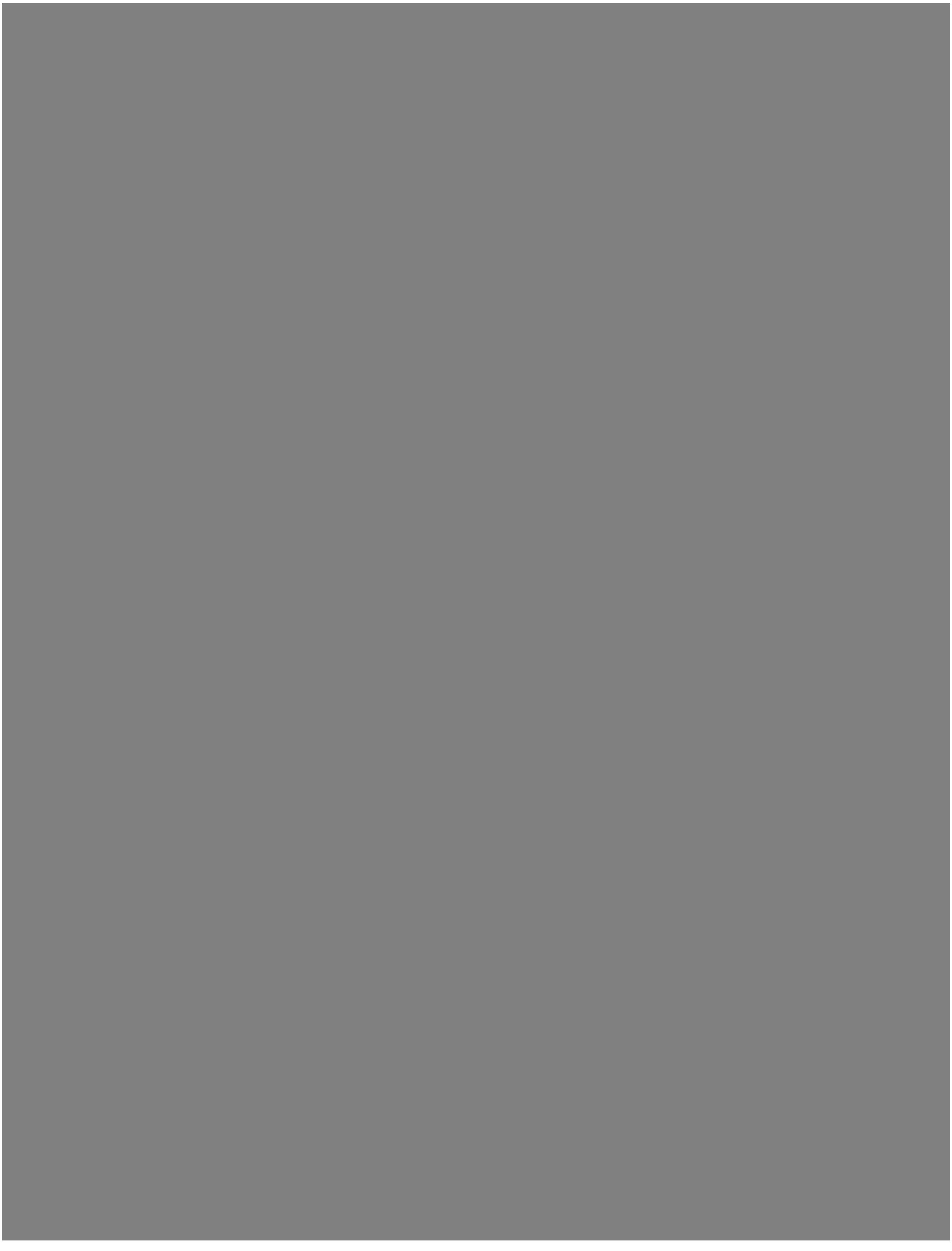


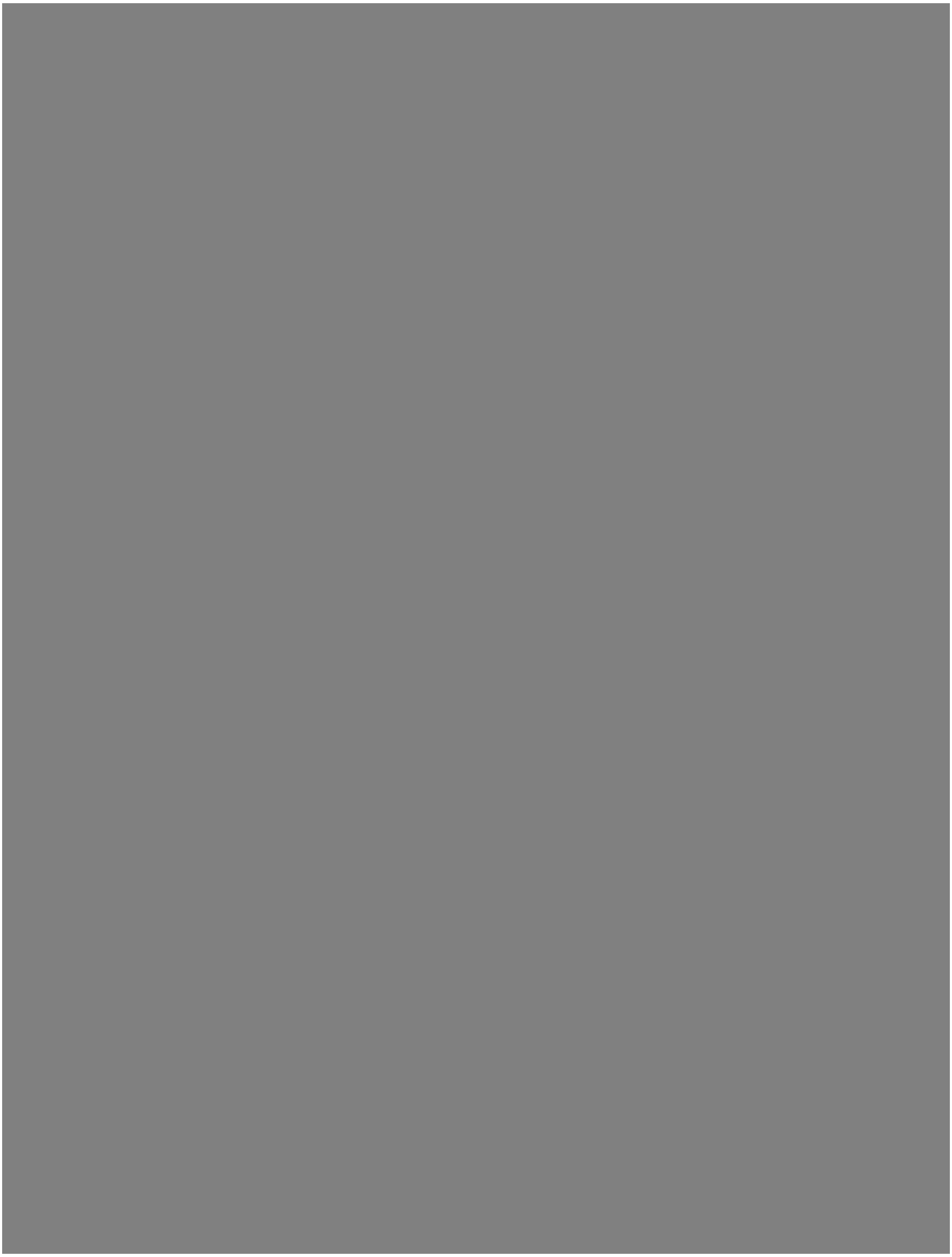












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