An Adaptive Teachable Robot For Encouraging Teamwork

by

Parastoo Baghaei Ravari

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2020

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Social robots used in education can take different roles, including tutor robots and peer robots. Peer robots (also called teachable robots) take the role of a novice in a teaching interaction while the students take the role of the teacher. Teachable robots leverage learning by teaching, which has been shown in prior research to increase the students' learning effort and time spent on the learning activity, leading to enhanced student learning. The concept of teachable robots has previously been applied for one-to-one interaction, however, to date, few studies use teachable robots in a group setting.

In this thesis, we developed an adaptive learning algorithm for a teachable robot that encourages a group of students to discuss their thoughts and teaching decisions during the tutoring session. We hypothesize that the robot's encouragement of group discussion can enhance the social engagement of group members, leading to improved task engagement, learning and enjoyment. The robot adapts to the students' talking activity and adjusts the frequency and type of encouragement. The robot uses reinforcement learning to maximise interaction between the students.

The proposed approach was validated through a series of studies. The first pilot study was performed in an elementary school and observed the interactions between groups of students and teachable robots. The main study investigated the feasibility of an adaptive encouraging robot in a remote setting. We recruited 68 adults, who worked together in pairs online on a web application called Curiosity Notebook to teach a humanoid robot about the classification of rocks and minerals. We measured social engagement based on the communication between group-mates, while the metric for task engagement was generated based on the users' activities in the Curiosity Notebook.

The results show that the adaptive robot was successful in creating more dialogue between group members and in increasing task engagement, but did not affect learning or enjoyment. Over time, the adaptive robot was also able to encourage both members to contribute more equally to the conversation.

Acknowledgements

I would like to thank Dana Kulić, for her guidance and mentorship throughout my graduate studies. She is an exemplary researcher and an incredible supervisor. I'm fortunate to have had the opportunity to work under her supervision allowing me to learn so much from her, both in robotics and in academic research principles.

This thesis would not have been possible without Edith Law, she has provided me with countless opportunities during my studies and working with her on her project has shaped my graduate school experience. She has supported me all along and provided me with the tools and facilities I required to complete my research during an unprecedented time.

Thank you to William Melek for being my co-supervisor and reading my thesis manuscript. Your feedback on my thesis is much appreciated. I would also like to thank Kerstin Dautenhahn for her time in reviewing my thesis, I value her insights and guidance.

I would like to thank all my colleagues and friends in the Adaptive Systems Lab, RoboHub and the HCI lab for their generous support. I'm grateful to have worked alongside you. Thank you for helping and motivating me to be a better researcher.

I would like to express my sincere gratitude to my longtime friends and my friends at the University of Waterloo. You were always there for me and didn't hesitate when I needed your help. I would also like to thank all of the amazing participants who took part in my user study and allowed me to complete my research.

Last but not least, I like to thank my family, I've appreciated your emotional support throughout my life, but especially during my graduate studies, thank you for your consistent love and encouragement.

Dedication

This work is dedicated to my grandmother, I have always felt her love and support from miles away and my parents who believed in me when I found it hard to do. I wouldn't be where I am if it wasn't for you.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Robots in education have demonstrated great potential for improving learning, enabling students to improve their self-esteem [7] motivation [31], and engagement [46]. While robots can take a variety of roles [7], teachable robots—robots that take the role of a novice taught by students—leverage learning by teaching to further enhance student learning. The idea is that teaching an agent can induce the so-called Protégé Effect [14], i.e., students learn better by teaching others due to increased effort, spending more time on the teaching activity and an increased sense of responsibility [14, 76].

While pedagogical research highlights the importance of group interaction and engagement on students' learning and overall performance in school [1, 24] and group interaction is frequent in classrooms, many of the research experiments involving teachable robots are based on one-to-one interaction with the robot [5, 11, 31, 41, 46, 49]. Even in studies occurring in group settings (e.g. studies in classrooms), only one student teaches the robot during each teaching session and there is a general lack of discussion of group dynamics and its effects on the students' experience [29, 66, 87]. In order to address this gap, we examine group interactions in social robotics and study the effect of social engagement on the learning experience.

In this thesis, we developed a teachable robot that dynamically adjusts its behaviour to the communicative activity of a pair of users. The robot encourages social engagement by inviting the users to discuss their thoughts and decisions with their group-mate. The frequency and style of the robot's encouragement are decided by a reinforcement learning (RL) algorithm based on a reward signal that encourages group communication, measured from the users' real-time audio input. We hypothesized that the adaptive robot will increase users' social engagement, improve their communication, and allow for equal contribution from each group mate. The feasibility of the teachable robot system and different characteristics of the robot (curious and fast learner) were tested in multiple pilots and simulations prior to the user study.

1.1 Contributions

We introduced an adaptive algorithm for encouraging social (group) engagement to analyze group interactions in a learning context with adaptive teachable robots. Our work is one of the few studies in the teachable robots domain that observes social interactions and is distinguished from the previous work because users not only work in dyads but social engagement is adaptively encouraged.

This work also provides an approach for physical teachable robots to be integrated with a web-based learning platform. The system was examined in a case study (pilot) and the results of users' interaction with the physical robot could be used to improve the design of future physical robots.

We performed a user study (N=68) to assess the effects of adaptive encouragement on increasing group (social) engagement and its effects on learning. We analyse the impact of encouragement on a range of factors, including social engagement, task engagement, knowledge gain (measured immediately after the experiment), as well as participant-reported measures such as enjoyment, group work dynamic, perception of the robot, mood and motivation.

1.2 Thesis Outline

This thesis is organized into the following chapters:

Chapter 2 presents a review of the literature relevant to this thesis.

Chapter 3 introduces the experimental setup, the humanoid robot and the web application used for the pilots and user studies.

Chapter 4 defines the adaptive learning algorithm used in creating the adaptive teachable robot.

Chapter 5 presents the pilots and simulations conducted to test the performance and feasibility of the system and the experimental setup.

Chapter 6 includes the details, the measures and the results of the online user study.

Chapter 7 discusses the limitations, a few possible directions for future work and conclusions.

Chapter 2

Literature Review

Robots in education have demonstrated great potential to assist the student learning process [7] and improve social skills [58]. Robots used in education can take on different roles during the learning process, which could be a tutor, a peer, or a novice peer [7]. When the robot takes the role of a novice, it can be teachable, in this case, the robot can also be called a teachable robot. In this chapter, we first summarise the literature on social robots used in education. Afterwards, we focus on teachable (novice) robots and their characteristics. Teachable robots are less knowledgeable robots and require the student user's help in learning. Moreover, we discuss the literature around adaptive robots and the benefits of adaptability. Lastly, we discuss the use of robots in groups of users to influence group dynamics. The experimental studies discussed in this chapter are summarised in three tables. For studies using robots as a peer (same level of knowledge as students) refer to Table 2.1, for studies with teachable robots, refer to Table 2.2 and for case studies refer to Table 2.3.

2.1 Social Robots in Education

According to research on social robots in education, incorporating social behaviours in robots, such as expressiveness, can improve the learning gain for students [60]. The benefits of the human-robot interaction for the students are affected by the social attributes of the interaction, such as gaze, spatial arrangement, expression of emotions and voice tone [34, 36, 49, 87] and robots should show a degree of adaptability to be considered social [25]. Using social robots has the potential to increase accessibility for students because learning can happen outside of the classroom [41].

The social aspects of the robot are enhanced by its physical embodiment. Physical robots can be used in lessons that need physical interaction with the world, such as pushing or touching [7]. Comparing virtual agents and physical robots revealed that embodied robots get more attention from the students which could increase their engagement [48] and students had a more positive perception (e.g. likability and trustworthiness) of physical robots [77].

Initially, most of the focus was on designing robots to tutor students or being a teaching assistant in the classroom. Recently, more researchers have studied the relationship between robots and students [7]. There are additional benefits of increased engagement from making the robot take a peer role, rather than a tutor [87]. Furthermore, some researchers aim to increase the benefits of social robots in education by relying on the Protégé Effect [32].

2.2 Teachable Robots

Studies in education and human-computer interaction (HCI) have already shown teaching boosts learning, understanding, and recall of the material [14], also known as the Protégé Effect. Teachable robots are novices that allow the users to take on the teaching role [7] and elicit the protégé effect, which increases students' effort [14] and improves learning [68]. Teachable robots can keep students engaged for longer periods [31, 46] and a study shows that students were motivated by taking the role of the teacher [31].

Teachable robots need to show their learning progress and improvements to increase students' task performance and learning. A study comparing robots in two conditions, "learning" and "non-learning" illustrates the importance of the robot's demonstration of learning [12]. In the study, the students corrected a humanoid robot's handwriting over the span of 4 weeks. The results indicated that the robot showing learning positively influenced the student tutor's writing ability and performance compared to the "non-learning" robot.

2.3 Adaptive Teachable Robots

Characteristics of the teachable robot can be designed to be adaptive [7, 8, 25]. Robots that adapt to the educational level and performance of the students led to greater learning gains [7, 41] and task performance [73] in comparison to robots that do not adapt. Robots with adaptive characteristics (e.g. dynamically changing voice, knowledge progression, verbal and non-verbal social behaviour) increase social presence [49], and learning gains [5].

To investigate the effects of adaptive social responsiveness and voice on learning, Lubold et. al. [49] performed a study with a peer robot that conveyed emotional information with its manner of speaking. The robot, Quinn, was designed to adapt its tone, intensity and speaking rate to that of the students. The results showed participants had the highest social presence (defined as the perceptual illusion of non-mediation) when the robot used both social dialogue and an adaptive voice. However, there was no significant effect on learning gains. The experiment was conducted with three conditions: (1) a social robot condition (social) with social dialogue content in addition to the educational content, (2) the addition of voice adaptation (social + voice), and (3) the (control condition) was a robot with neither social dialogue nor voice adaptation. They observed a correlation between the number of retaught attempts and learning, as well as social presence and learning.

A study on personalization [5] compared a personalized and non-personalized robot in two different classrooms. The learning task was administered through a tablet. The personalized robot differed in non-verbal behaviour (gaze and movement), friendliness (e.g. calling the children by their name), and adapted its progression (responsiveness) to the students. The students showed significantly increased learning when using the personalized robot. However, despite the robot being in a classroom, the robot only supported one-on-one interaction and the turn-taking was moderated by the teacher.

2.4 Group Interaction

Group interactions are rare in studies of teachable robots in education [29,66,87], and such studies do not tend to discuss the effects of group interaction on the experiment results. Zaga et. al. [87] show additional benefits (e.g. increased engagement) from the robot taking a peer role, rather than a tutor, their participants included 10 pairs of students, however, there is no discussion about the group aspects. Tanaka et. al. [66] worked on developing an educational application for the humanoid robot Pepper. They defined three games which were designed to take advantage of care-receiving robots (CRR) and total physical response (TPR), the children play the games in groups but no more information is provided. Hood et. al. [29] observed group-mates giving each other advice while teaching a humanoid robot handwriting. This collaboration occurred naturally without the researchers' or robot suggestions.

Outside of educational HRI research, there have been studies attempting to manipulate human team dynamics, performance, and perception of group cohesion during human-robot interaction [64, 69, 80].

A study by Werry et. al. [80] uses a robot as a mediator for autism therapy. The children work with the robot in groups of 2 and they observed shared attention and social interaction in one trial. They concluded social robots have the potential for changing non-social plays (a child playing alone), to non-interactive (both children playing with the robot without any social interaction) and eventually to interactive and social play. They suggested the need for further two-children-one-robot interaction.

Micbot [69] is a microphone robot that was used to shape the group dynamics and team performance in a game context. Micbot was a non-participant in the team and influenced the team either by back-channelling or encouraging the least active member to join the discussion. Micbot also incorporated movements to turn toward the speaker when they talked. The results showed that the robot with encouraging behaviour and matching movements (instead of random movements or no movements) balanced participation, and improved group task performance.

Outside of the context of social robots, adaptability has been used to increase engagement in group settings. Meng et al. [52] explored the idea of a robotic "Living Architecture System" (LAS) [6] automatically adapting to a group's preferences in an experiment conducted within a museum exhibition. The reward for the reinforcement learning (RL) algorithm was user engagement, which was measured with ambient sensors. The results of the experiment showed that the RL-selected robot actions could increase engagement.

In contrast to these prior works, our teachable robot adaptively encourages group engagement to shape group dynamics and is personalized to the groups' social engagement behaviours during the course of interaction.

Table 2.1: Summary of Controlled Studies for Peer Robots

Study	Task	Robot	Independent Variable	Dependent Variable(s)	Measurement
Kory et al. [41]	language learning	Dragon-Bot	Adapting story level vs. Not adapting story level	1) New words learned 2) Complexity & style of stories 3) Similarity	1) Vocabulary test 2) Story length, Flesch-Kincaid grade level 3) CohMetrix
Wainer et al. [75]	video game	Kaspar	Interaction with human before interacting with the robot vs. After the robot*	collaboration in the context of a cooperative video game	1) In-game actions: choosing (expressing desire), successful shape selection (simultaneously choosing), unsuccessful shape selection 2) Coding videos: prompting, positive affect, gaze and gaze shift, choosing (verbally)
Kory et al. [42]	language learning	Dragon-Bot	Easy robot stories vs. Hard stories*	Language improvement in stories	Story length Vocabulary test
Zaga et al. [87]	puzzle game	Nao	Peer vs. Tutor	Task Engagement in 3 categories 1) Cognitive: focus. 2) Behavioral: task performance 3) Affective: enjoyment	1) Behavioral & Gaze observations 2) Task completion percentage & duration 3) Enjoyment questionnaire (IMI)
Lubold et al. [49]	math	Quinn	Social + voice-adaptation, Social Behaviours, Control Condition (3 conditions $\times$ 2 genders)	1) Rapport and Social presence 2) Persistence 3) Learning Gain	1) Likert-scale questions, Networked Minds Social Presence Inventory 2) Re-taught attempts. 3) Pre and Post-Study knowledge test
Baxter et al. [5]	math & classification	Nao	Personalized vs. Non-personalized	1) Learning gains 2) Perception	1) Pre- and post knowledge test, within-interaction performance data, class exams 2) Intrinsic Motivation Inventory (IMI), Perceived Social Support, Networked Minds Social Presence

* within-subject (all other studies are between-subject)

Table 2.2: Summary of Controlled Studies for Novice Robots

Study	**Task**	**Robot**	**Independent Variable**	**Dependent Variable(s)**	**Measurement**
Tanaka et al. [68]	verb learning	Nao	Care-receiver robot vs. No robot*	1) Learning 2) Teaching forms	1) Pre & post-study knowledge test 2) Coding videos
Johal et al. [36]	hand-writing	Nao	Spatial arrangement*	1) Performance 2) Robot's score 3) Engagement 4) Perception of robot's learning 5) Persistence	1) Response time, writing time 2) Euclidean distance between letters 3) With-me-ness 4) Total student feedback (+1 or -1) 5) Number of demos per word
Walker et al. [77]	math	Quinn	Embodied Robot vs. Virtual agent	1) Learning gains 2) Perception	1) Pre & post-study knowledge test 2) Godspeed Questionnaire
Lindberg et al. [48]	math	Epi	Virtual agent vs. Physical robot *	1) Engagement 2) Perception	1) Observational protocol 2) Godspeed questionnaire
Chandra et al. [12]	hand-writing	Nao	Learning robot vs. Non-learning robot	1) Awareness of robot's Grades 2) Perceived robot's performance 3) Impression of the robot 4) Perceived robot's role 5) Self-efficacy in tutoring 6) Learning gains	1,2,4,5) Interviews 3) Godspeed questionnaire (modified) 6)Pre, post-study tests
Yadollahi et al. [85]	reading	Nao	Deictic gestures (2) × Types of mistakes (3) × Level of reading (2)*	Correction percentage	Correction count percentage (True Positive + False Positive)
Chaffey et al. [10]	math	Nao	Side-by-side vs. Face-to-face F-formations	Comfort, Attention Engagement, Motivation Physical Proximity	Post-study Survey

* within-subject (all other studies are between-subject)

Table 2.3: Summary of Case Studies

Study	Task	Role	Robot	Study Goal	Measurement
Kanda et al. [38]	language learning	peer	Robovie	Investigate the effects of the robot on encouraging learning	English test score Duration Time spent in interaction vs. friends Pre and post study test
Tanaka et al. [68]	verb learning	novice	Nao	Will the number of mistakes the robot makes invoke care-giving behaviours in children	Coding videos
Hood et al. [29]	hand-writing	novice	Nao	Observe the children's interaction with the robot	Duration of interaction Number of demonstrations
Tanaka et al. [66]	language learning	novice	Pepper	Validate the system	Observations
Lemaignan et al. [46]	hand-writing	novice	Nao	Study the engagement and performance of during the interaction	Experiment duration Number of demonstrations Correlation between student's feedback and robot's mistakes Interviews and follow-up updates With-me-ness
Jacq et al. [31]	hand-writing	novice	Nao	Validate the system. In addition, one case study investigated the effects of the robot's progress on student's feedback and progress	Number of demonstrations Experiment duration Demo writing time Parent's interview

2.5 Summary

Robots in education with the ability to adapt and provide personalised interaction can provide additional benefits for their users in comparison to non-adaptive robots . The studies reviewed showed positive feedback and greater learning in the case of adaptive robots. The adaptive algorithm we employ adapts the robot's group engagement encouraging actions.

For the robots to be more social and utilize the embodiment of the robot and its potential to outperform virtual agents, they can be designed to express emotions through body movements. The results of experiments on robots' behaviours show that curiosity, interest and deictic gestures increase the students' motivation, engagement and result in an overall more positive teaching experience. Our humanoid robot accompanies its dialogue with appropriate movements that could be neutral, happy, sad, curious and bored.

Most of the literature on social teachable robots focuses on individual student's interaction with the robot in contrast to the natural classroom setting in which the student is not in isolation. The education literature also points out the benefits of social engagement and collaboration on learning while robots have demonstrated some potential for being a moderator for collaboration. Therefore, teachable robots used in group settings demonstrate a potential for increasing engagement, sense of group inclusion and learning.

Chapter 3

Experimental Setup

To evaluate the idea of a teachable adaptive robot and investigate the effects of adaptive social engagement encouragement on learning, we developed an experimental setup for a group human-robot teaching interaction. The proposed experimental setup consists of three main components detailed in the sections of this chapter. The first component is a web application called Curiosity Notebook [44, 45], which we adapted for this study. The second component is an adaptive encouragement algorithm with audio data as the reward signal, the algorithm is detailed in Chapter 4. The last component is a NAO V6 [1] Humanoid robot (as seen in Figure 3.4) from Softbank Robotics, which is connected to the Curiosity Notebook.

3.1 Curiosity Notebook

The Curiosity Notebook [44,45] enables users to read articles on various topics, structured as taxonomies, and teach the robot about them. Figure 3.1 shows the Curiosity Notebook interface during the task of rock classification. The users start the conversation by clicking one of the interactive buttons. There are two categories of buttons to interact with the robot: the *teaching* buttons and the *checking* buttons. Amongst the teaching buttons, users can use the *describe* button to teach the agent about an object's features, the *explain* button to explain the feature and the *compare* button to discuss similarities or differences between rocks. After the user clicks any of the three teaching buttons, the robot guides the interaction by asking different types of questions to learn about the features of a sample

[1] https://www.softbankrobotics.com/emea/en/nao

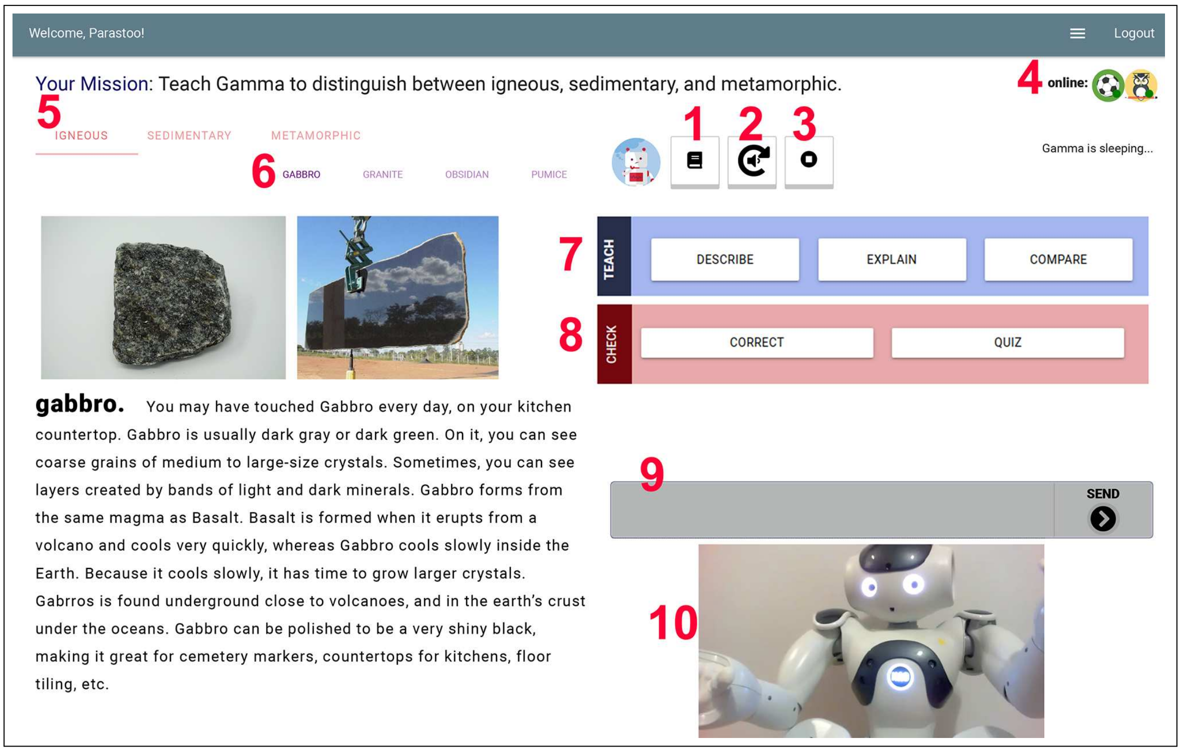


Figure 3.1: Curiosity Notebook with Zoom, 1: Robot's Notes, 2: Repeat Request 3: End Teaching, 4: Online Users, 5: Categories, 6: Example Articles, 7: Teach Buttons, 8: Check Buttons, 9: Chat Window, 10: Zoom window of Gamma's video

rock in a specific category. The conversations initiated by each button are associated with a state machine. A detailed diagram of the *Describe* button state machine is shown in Figure 3.2. The yellow states indicate where the encouragement of collaboration was added with an adaptive algorithm. The robot first starts the conversation and asks for the user to pick a rock and introduce it. If the rock is new for the robot, it will ask for the rock's category, and then move on to ask questions about features of the selected rock. If the rock is already known, the robot immediately moves on to asking for more features about the rock. The robot only proceeds to the next state after each user input if the state is valid, otherwise, the robot gives the user a second chance to respond. At the end, the robot communicates its feelings and excitement about learning. No other interactive buttons can be clicked until the state machine for the current button has reached the termination state. The *checking* buttons are for testing the robot's learning. The users can choose to either *quiz* the robot by asking it to categorize an object or *correct* a previously learned concept in the robot's notes. The users can read and move between the categories and articles of each category at any time.

There are also three special-function buttons. Unlike the interactive buttons, the special-function buttons are all single action with no states and can be clicked at any time. The first button is the *Robot's Notes* button. Clicking on the Robot's Notes button brings up a notebook containing notes of all the knowledge that the robot has learned so far. The *Repeat* button can be used by users in case they misheard or did not hear the robot. The *End Teaching* button allows the users to indicate that they have finished the teaching process. Users can choose to stop teaching at any time.

The Curiosity Notebook supports group or one-on-one interaction. In our work, the group mode (for a pair of users) was used, in which case the Curiosity Notebook uses automated turn-talking to facilitate social interactions. In the turn-taking mechanism, one user will be the active teacher; only the active teacher can chat with the robot. The second user can click on different articles or use any of the special-function buttons. The turn-taking was shown to be effective in moderating the conversation during our initial pilot (discussed in Chapter 5, Section 5.1). The Curiosity Notebook can be used on its own or connect to a physical robot. For our study, we used the Curiosity Notebook with a humanoid robot. The connection to the robot is described in section 3.3.

3.1.1 Curiosity Notebook, Early Version

An early version of the Curiosity Notebook was used in the first in-person pilot detailed in Chapter 5. In this early version, the teaching task started by the user choosing a

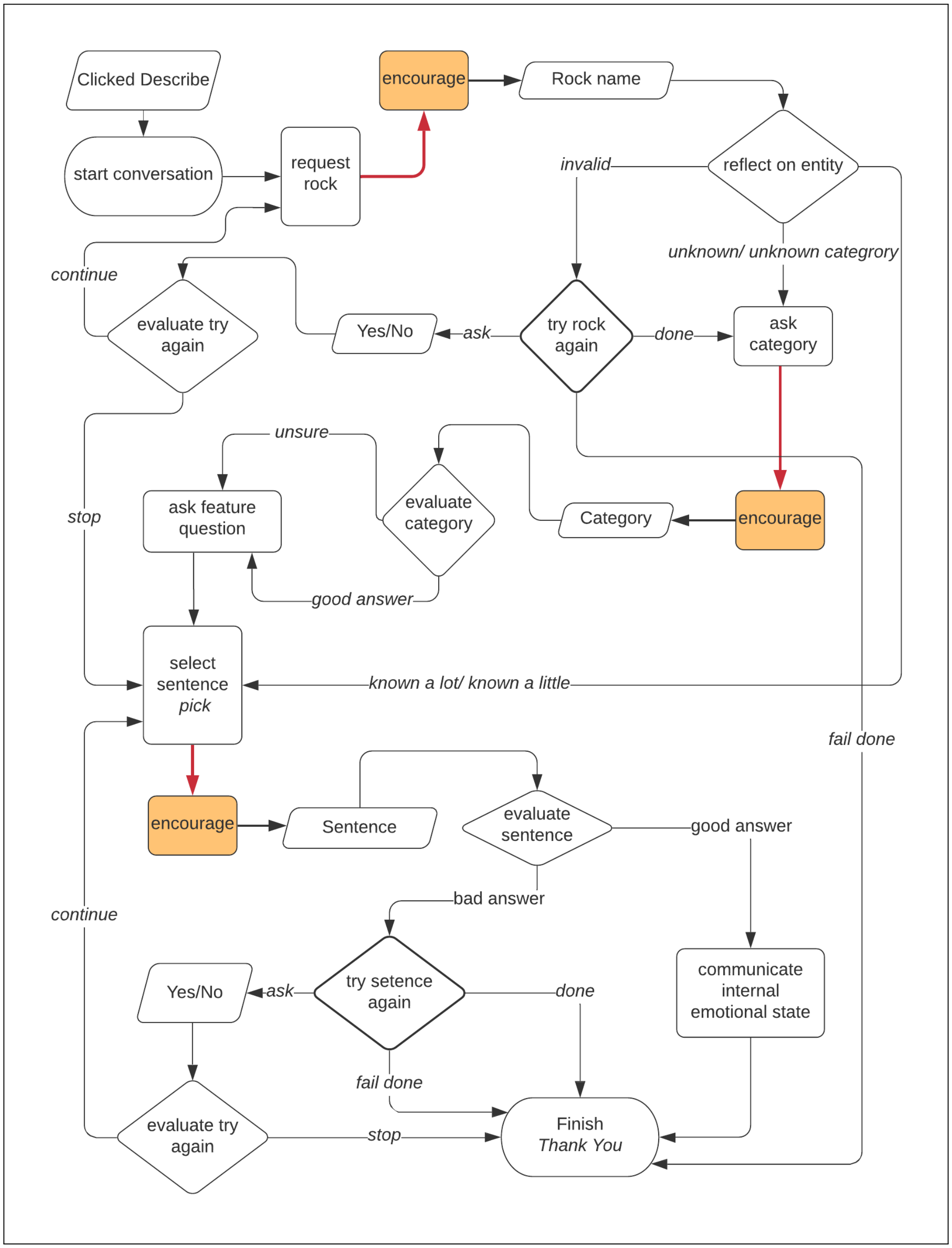


Figure 3.2: The state machine that is executed after the Describe Button is clicked

topic (choice between Arts, Animals, and Rocks), then picking an object for the robot to learn about. The flowchart of the chat interaction is available in Fig. 3.3. After the user registered an object, the robot would ask them to select a sentence from the available articles, to teach the robot about a feature of a category. Then the robot proceeded to ask questions about the sentence (immediate questions) and/or deeper questions about the category. Examples of the questions are given in Table 3.1. The first three are immediate types and the last three are deeper questions. There was no adaptive element in this pilot, the maximum number of questions the robot could ask was 4 and the type of question was chosen randomly. After the robot asked the questions, the robot proceeded to either ask for a fun fact about the category/object, tell a joke or ask how well it's performing (validation question). The list of validation questions is also provided in Table 3.1. In the final step, the robot indicated that it has learned the targeted feature, and one of the progress bubbles on the notebook interface would be filled. The cycle was repeated for all the subsequent features. Each topic has between 8 to 10 features before the robot can classify all the objects of that topic into the three categories covered in the lesson. The robot also responded to each of the answers the students provide to its question. The emotional tone of the response depends on the robot's understanding and personality. The emotion is also conveyed through NAO animations as discussed in Section 3.3. The robot's personality had two variables, curiosity level (low or high), and learning speed (slow or fast).

3.2 User Audio Input

Capturing the audio input of the users requires either two different channels (for in-person studies), or the use of speaker diarization (the process of partitioning audio based on speaker identity). For our system, we developed both techniques but found that using different microphones for two users showed better performance. The voice activity of each microphone was set to the noise level of the room and a Voice Activity Detection (VAD) algorithm was used to capture the duration of voice activity. The Python interface for WebRTC[2] VAD was used in our system. During the remote experiments (as described in Chapter 6), the voice activity was coded manually in real-time as we couldn't develop a reliable Zoom audio speaker diarization technique. The VAD algorithm however was still used for data analysis after the experiment.

[2] https://webrtc.org/

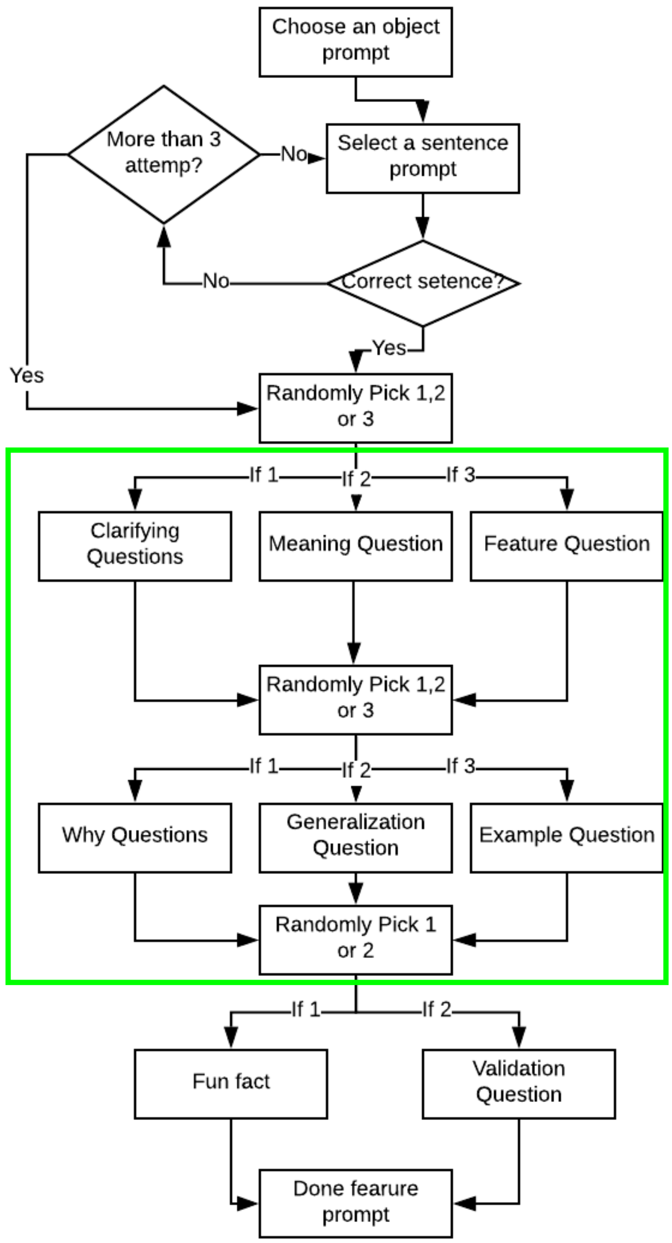


Figure 3.3: Flowchart of interaction between a robot and a group of students for learning a feature. The stages in the green box are the focus for reinforcement learning.

Table 3.1: Example of Question Types in the task of Animal Classification

Clarifying Question	What does cold-blooded mean?
Example Question	What is an example of an insect?
Why Question	Why are dogs mammals?
Meaning Question	Can you give me more examples of reptiles?
Feature Question	Do dogs have fur covering them?
Generalization Questions	Do all mammals have four legs?
Validation Questions	Am I smart? Am I a good student? Am I learning? Do you think I learned well? Will I do well in a test? Am I still good at learning? How do you think I am doing? Good or bad? Do you think I will ace the test? Do you think I know more now than before?

3.3 The Humanoid Robot

The robot connects to the Curiosity Notebook via a Postgres database provisioned on the Heroku platform, such that each robot utterance is sent to the database and then to the robot. In addition to the text of the dialogue, each sentence is coded with an emotion: happy, sad, baseline, bored or curious. Most of the robot's sentences are neutral. The emotion code is happy if the robot just learned something (e.g. "I love learning about rocks"). Sentences are coded as sad if the robot makes a mistake during the quiz. The emotion is *curious* with a 50% probability if the robot is asking a question, and a sentence is coded *bored* if the notebook was idle for more than 2.5 minutes, in which case the robot asks participants to continue teaching. The emotion coding was also used to select the appropriate movement for the robot. The majority of the motions were predefined in naoqi, the operating system of NAO V6 robot, with a few additional nod motions, developed manually by joint manipulation for the neutral category. The movements are summarized in Table 3.2. The utterances are spoken out by the robot while it is acting the corresponding movement.

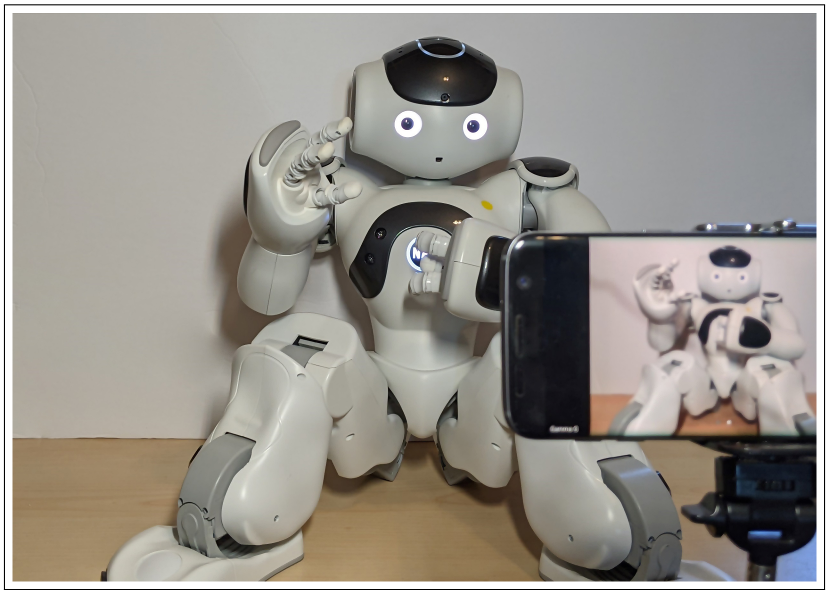


Figure 3.4: The humanoid robot during a Zoom call

3.3.1 The Humanoid Robot for the In-Person Pilot

During the in-person studies, the robot also had some physical capabilities that we couldn't utilize in the online user study. The Nao robot has cameras that we used for reading barcodes of objects. However, in one of our pilots, we noticed the robot head movements interfered with its ability to read barcodes, therefore, we added the option for users to type the name of the object they picked or to click on the object in the web interface. The robot also has speech recognition that wasn't performing as expected and we didn't use it for the pilots. We also developed a way to communicate with the robot outside of the web interface using touch. The robot was able to receive feedback by touching, a pat on the head was used as an encouragement signal (when the robot was correct or was doing a good job) and a tap on the hands was a signal to let the robot know it made a mistake. The foot sensors were used to activate vision and speech recognition explained above.

Table 3.2: Robot's Movements

Emotion	Sample Movements
sad	Scared, frustrated, hurt, sad, crying, and getting shy, looking down
happy	Laughs, giggles, excited noises such as "Yoohoo", clapping sounds,
neutral	Hands and head movements while talking. Sneezing, Eye contact and turning its head to indicate listening,
curious	Recalling and Thinking motions, for example scratching its head, putting a hand under its chin.

Chapter 4

Adaptive Encouragement

This chapter starts with a brief background on Reinforcement Learning and specifically Q-Learning. The background is followed by details of our Q-Learning algorithm designed to encourage group collaboration, how the algorithm is rewarded and how the users are encouraged. The chapter ends with our proposed research questions and hypothesis.

4.1 Q-Learning Background[1]

Reinforcement learning (RL) algorithms map each state (defined as the representation of the environment at a given time) to an action that changes the environment based on the rewards associated with each state and action. The goal is to learn the most rewarding action for each state and maximize the total reward received. The value function of an RL algorithm keeps track of the long-term desirability of states, calculated by predicting future rewards. The mapping learned by the RL algorithm is called a policy. Q-Learning is an off-policy and model-free reinforcement learning algorithm [65]. Model-free RL is used when we don't have an accurate model of the environment therefore we can't predict the state that each action will lead to. Off-policy learning methods don't follow the learned policy while generating training data. Q-Learning keeps track of the best actions by updating a Q-table. The Q-table summarizes the rewards received for selecting each action at a particular state and is used for making future decisions (selecting actions). After each action, the appropriate value in the Q-table is updated based on the reward received according to the Q-function defined in Equation (4.1). Here, S_t indicates the state at the

[1] Based on Sutton, 2018 [65]

time t and A_t represents the action. The learning rate λ controls how fast the algorithm adapts the Q-table values. The discount rate γ controls how much the new reward matters versus the previous rewards when updating the Q-table value. The exploration rate (ϵ) is the probability ϵ with which the algorithm disregards its Q-table values for picking the best action and picks a random action instead.

$$Q(S_t, A_t) = Q(S_t, A_t) + \lambda[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)] \tag{4.1}$$

4.2 Q-Learning for Encouragement

Our goal is to increase group/social engagement between the team members using RL, hence, we modified the robot to deliver encouraging statements during the teaching conversation, specifically, after posing a question to the user and waiting for their answer. The states where encouragement can be provided are highlighted in Figure 3.2 in yellow. For creating an adaptive encouraging system, we use the Q-learning algorithm [79] to selectively choose if and how to encourage group engagement based on the users' talking activity. The reinforcement learning framework is defined as follows:

1. **States**: At each time step, the interaction can be in one of four states: a) there is not enough conversation, b) user A is dominating the conversation, c) user B is dominating the conversation, d) both users are equally and fully contributing.

2. **Actions**: There are five possible actions: encourage the active user, encourage the inactive user, encourage both users, pick a non-encouraging sentence, or say nothing.

3. **Rewards**: A weighted sum of the total time spent talking and the ratio of talking time of two users. The total reward is calculated as shown in Equation (4.5).

4.3 Reward Calculation

To calculate the reward of the Q-learning at each step, the algorithm reads the voice activity duration of both users (spk_1, spk_2) since the last reward calculation. The reward has two parts. The first part rewards more talking between both users (r_{talk}), which is calculated using the ratio of the total duration that both users spoke ($t_{talking}$) and the total time spent interacting with the robot (t_{total}). The second part rewards the ratio of

Table 4.1: Encouraging Sentences

Encouragement Type	Sentence
encourage the active user	"Make sure you let your partner know what you are thinking."
	"Try to explain your answer to your partner before telling me."
encourage the other user	"Why don't you ask if your partner agrees with you?"
	"Why don't you ask what your partner thinks?"
encourage-both	"Why don't you two discuss this?"
	"Can you two talk amongst yourselves first?"
	"Let's do this together team!"
	"You can discuss it together first."
	"We can discuss it as a team!"
	"Do you want to discuss if you both agree?"

how much the first user talks to how much the second user talks (r_{ratio}). Both parts of the reward (4.3) and (4.4) are calculated as their distance from the ideal value of 1 (i.e., the users spoke the full duration of the experiment and they spoke equally). The total is calculated by summing the two partial rewards and combining them as a cost ($c_{overall}$) by negation (4.5). The full algorithm is described in Algorithm 1. The state at time t is indicated with $state_t$ and the notation is consistent for actions and costs.

$$ratio = \frac{spk_1}{spk_2} \quad \text{and} \quad t_{talking} = spk_1 + spk_2 \tag{4.2}$$

$$r_{talk} = (1 - \frac{t_{talking}}{t_{total}})^2 \tag{4.3}$$

$$r_{ratio} = (1 - ratio)^2 \tag{4.4}$$

$$c_{total} = -(r_{talk} + r_{ratio}) \tag{4.5}$$

4.4 Encouraging Statements

There are three different types of encouraging statements, in addition to baseline non-encouraging statements, summarized in Table 4.1. The robot utterances were created following the techniques teachers use in their classrooms to promote class participation [62] and encourage cooperative learning and group discussions in the class [26]. Some utterances were targeted to individual users by calling their name to specifically engage them [51], or to ask them to engage their partner, while others were aimed at the group as a whole [57].

Algorithm 1 Q-Learning: returns an action

Require: $states[\,], actions[\,], \gamma, \lambda, \epsilon, Q_{table}$
Ensure: $size(actions) > 0, size(states) > 0$

$spk_1, spk_2 \leftarrow read\,audio()$
$ratio \leftarrow \frac{spk_1}{spk_2}$
$t_{talking} \leftarrow spk_1 + spk_2$
$t_{total} \leftarrow 10$

$\{$*Calculate the reward of last action*$\}$
$r_{talk} \leftarrow (1 - \frac{t_{talking}}{t_{total}})^2$
$r_{ratio} \leftarrow (1 - ratio)^2$
$cost_{t-1} \leftarrow -(r_p^2 + r_k^2)$

$\{$*Updating the Q-table*$\}$
if $t > 0$ **then**
  $Q_{table}[state_{t-1}, action_{t-1}] = Q_{table}[state_{t-1}, action_{t-1}]+$
  $\lambda \times (cost_{t-1} + \gamma \times max(Q_{table}[state_t]) - Q_{table}[state_{t-1}, action_{t-1}])$
  $sstate_{t-1} \leftarrow state_t$
end if

$\{$*Pick Future Action*$\}$
if $random\,number < \epsilon$ **then**
  $action_t \leftarrow pick\,random(actions[\,])$
else
  $action_t \leftarrow max(Q_{table}[state_t])$
end if
return $action_t$

4.5 Research Questions

In this work, we seek to investigate whether we can design an adaptive robot that can increase users' social engagement as measured by their communication. We also seek to understand how the adaptive robot affects the learning outcomes and the learning experience of the users. Our first hypothesis (**H1**) is that the robot encouraging teamwork will increase users' social engagement during the study, therefore increasing their communication. The second hypothesis (**H2**) is that the adaptive robot will have greater effects on (**H2a**) task engagement, (**H2b**) enjoyment and (**H2c**) learning in comparison to the baseline robot. Our third hypothesis (**H3**) is that adaptively encouraging teamwork will ensure both users contribute to the conversation more equally, without any user dominating the conversation.

Chapter 5

Pilots and Simulations

The experimental setup (the curiosity notebook and the humanoid robot) was first piloted in a classroom setting. In the pilot, we observed children interact with the robot and the curiosity notebook while updating the system. The pilot was reviewed and received ethics clearance through the University of Waterloo Research Ethics Committee (ORE#40392). In addition to the pilot, simulations were used to test the adaptive learning algorithm. The pilot and the simulation results are documented in this chapter.

5.1 Elementary School Pilot[1]

The goal of the elementary school pilot study was to validate the basic learning-by-teaching system, which includes the earlier version of the Curiosity Notebook connected to the humanoid robot. We chose to use the NAO humanoid robot (discussed in section 3.3) for the study following previous research that demonstrates the physical embodiment of the social robot carries additional benefits for the social interaction (as discussed in section 2.1). The system used in the pilot didn't record user audio as the robot wasn't designed to be adaptive or to encourage social interaction.

[1]Some results discussed in this section have been published. Law, Baghaei Ravari, Chhibber, Kulic, Lin, Pantasdo, Ceha, Suh, and Dillen. *Curiosity Notebook: A Platform for Learning by Teaching Conversational Agents* [44]

5.1.1 Study Design

The pilot study was carried out as an observational study in a local primary school from May to June 2019, one day a week, for a duration of 5 weeks. Participants included 7 females, and 9 males, with 11 students from the 4th grade and 5 from the 5th grade. The students were divided into 4 groups of three students, a group of two and 2 groups of one student. Each student was provided with a Chromebook to access the curiosity notebook. Each group was teaching one NAO robot. The NAO robot connected to the Curiosity Notebook as explained in Chapter 3. The sessions lasted 90 minutes. The pilot used the measures introduced in section 6.4, except it excluded measures regarding group work enjoyment and the familiarity with the group members.

In the first 4 weeks of the experiment, 4 groups of students (triads) were asked to teach the robot rock classification, animal classification and painting classification. In the first week, students were given a short introduction on the task, did the pre-study survey and proceeded to teach the robot animal classification. Researchers sat with each group to observe the students and answer questions during the interaction about the system, however, the children learned how to operate the notebook within the first 15 minutes of the interaction. Researchers also helped the students answer the pre-study and post-study surveys and knowledge tests. In the surveys, the students were asked about their familiarity with computers and robots, their perception of the robot and at the end, they were interviewed about their teaching experience. All the interactions with the Curiosity Notebook were logged in the notebook database. After finishing each topic (e.g. finishing animal classification) the students did the post-study survey. In the 5th week, the new students were also given a brief introduction of the task, except their interaction was only a single session. The results of this pilot are published in [44].

5.1.2 Lessons Learned

Students generally enjoyed the teaching experience. The post-study survey showed that students liked the robots and thought that it was fun teaching the robots.

In the first week of the pilot, the free-form interaction caused some students to be left out of the conversation, which led to the implementation of a fixed turn-taking structure. The students in groups of more than one had to take turns, the turns switched after a single interaction block. An interaction block is defined as one robot request, one student response and finally one acknowledgment of the response from the robot. Another downside to free-form interaction was that without the robot leads and questions, the students were not

Figure 5.1: The experiment setup, NAO and Laptops (Source: "Curiosity Notebook: A Platform for Learning by Teaching Conversational Agents" [44])

sure how to proceed with teaching. We decided to change the structure of the Curiosity Notebook so the robot always starts the conversation by giving some hint as to what questions should students answer next. However, in the post-study survey, the students expressed that they wished they had more choice in how they teach the robot, the latest version of the Curiosity Notebook includes multiple teaching options to give the users this freedom.

We also observed some group collaboration, some students took the initiative to offer help to their teammates during the teaching session, without any explicit robot encouragement of teamwork. This behaviour might also be motivated by students' eagerness to get their own turn. Groups progressed through the task at different speeds and they also had different approaches to when they wanted to quiz the robot. Some groups only quizzed the robot after they finished teaching, while others quizzed the robot multiple times throughout the teaching session. Additionally, it was observed that in a group setting, the amount of attention the robot gave each student affected students' perception of their own teaching ability. The students also noticed the teachable robot's social characteristics such as calling the students by their names and looking in the student's direction.

After analyzing the responses to the validation questions, we concluded they are positively biased (37 positives vs 7 negatives and 3 mildly negatives e.g. "not good enough yet"). This phenomenon has been discussed in other literature [70], students might have felt bad if they didn't reward the robot, even when the performance was not great. However, one group constantly gave negative feedback to the robot. This might be due to curiosity for observing the reaction of the robot to feeling sad or hurt. The question combinations generated by the robot were limited to a maximum of 4 questions and they were generated at random. Answers to the validation question depended on the group rather than the robot's actions (e.g types of questions the robot asked, as detailed in Table 3.1 in Chapter 3) and they remained similar regardless of the robot's characteristics (e.g. asked different questions, learned faster or slower, showed more or less curiosity). Considering the results, the final version of the Curiosity Notebook didn't include validation questions.

Additionally, over time we saw children focused more on the Curiosity Notebook and less on the robot, reducing the outside-notebook interactions with the robot, such as talking directly to the robot, giving the robot touch feedback and showing objects to the robot. This observation led to changes in the system such as removing spoken sentences of the robot from the chat log (adding a repeat button instead) and improving the synchronization of the Curiosity Notebook and the robot (the Curiosity Notebook only updates after the robot is done speaking or moving). The students also rarely used the tactile touch feedback.

5.2 Simulations

Simulations to test the adaptive learning algorithm were conducted by assuming a simplified model of a pair of participants. The simulations were used to validate the learning code and select learning hyper-parameters. Two models of the participants were tested and the results are explained in this section.

Simple Dyad Model: The model (also described in Algorithm 2) generated values for voice activity for both hypothetical participants that start from a random value between 0 to 1 second in the 10-second measurement interval. The simulated participant's voice activity in the next measurement interval is generated based on the action of the adaptive learning algorithm. If the algorithm picks the action of encouraging participant #1, the voice activity of that participant would be increased between .5 to 2 seconds, we call this the growth rate. Likewise, if participant #2 is selected, the corresponding voice activity increases. If the algorithm chooses to encourage both participants, the voice activity of both participants will grow with different random growth rates. Any other action results in a growth rate of 0. Random noise was also added to the participants' voice activity, ranging between -1 to 1 second in each measurement interval. The interaction consists of 40 measurement interval. The upper-bound for the growth rate has a natural decay, given that the participants might talk less as the time passes, the decay 0.01 second for each measurement interval (e.g. participants' voice activity growth rate can only be between 0.5 and 1.99 seconds after the first round). The model also makes sure the generated values for each participant are within acceptable limits of time, no generated voice activity value can be less than 0, or more than 5 seconds for each participant. This dyad model favours the action of encouraging both participants and then the action of encouraging any of them, as expected the algorithm trained with this model converges to picking one of these actions over and over again.

Algorithm 2 Simple Dyad Model

Require: $speaker1_{t-1}, speaker2_{t-1}, action_{t-1}, round$
  $noise_1 \leftarrow random(-1\ to\ 1)$
  $noise_2 \leftarrow random(-1\ to\ 1)$
  $decay \leftarrow 0.01 * round$
  $growth_1 \leftarrow random(0.5\ to\ 2 - decay)$
  $growth_2 \leftarrow random(0.5\ to\ 2 - decay)$
  if $action_{t-1} = encouraging\ speaker\ 1$ **then**
    $speaker1_t \leftarrow speaker1_{t-1} + growth_1 + noise_1$
  else if $action_{t-1} = encouraging\ speaker\ 2$ **then**
    $speaker2_t \leftarrow speaker2_{t-1} + growth_2 + noise_2$
  else if $action_{t-1} = encouraging\ both\ speakers$ **then**
    $speaker1_t \leftarrow speaker1_{t-1} + growth_1 + noise_1$
    $speaker2_t \leftarrow speaker2_{t-1} + growth_2 + noise_2$
  end if
  return $speaker1_t, speaker2_t$

As explained in Chapter 4, Equation (4.5), the desired value for the cost (reward) in our adaptive learning algorithm is 0. The value of the cost (total reward) is plotted based on an average of 100 trials. To tune the adaptive learning algorithm, we ran 100 trials for each value of the learning rate (λ), the discount rate (γ), and the exploration rate (ϵ) between 0.1 and 0.9, in 0.1 increments. The results of the grid search for (λ), (γ) and (ϵ) are shown in Figure 5.2, Figure 5.3 and Figure 5.4 respectively.

As we see in the simulation results, the highest exploration rate performed the best, because when the interaction is short (40 intervals) and the costs are always negative, the algorithm won't explore the Q-Table at all if the Q-Table is initialized with values less than the highest possible cost (-2 in our algorithm) as they will appear to be worse choices than the already explored actions. When the Q-Table is initialized with values that

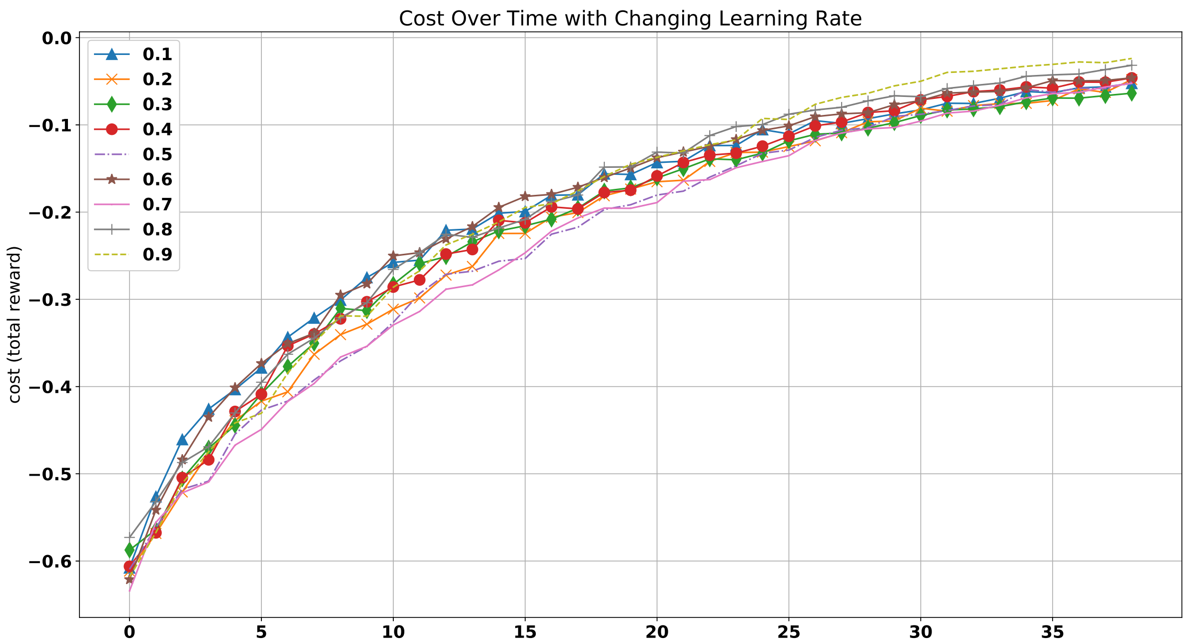


Figure 5.2: Simulation Results of Grid Search for The Learning Rate (λ), using Simple Dyad Model

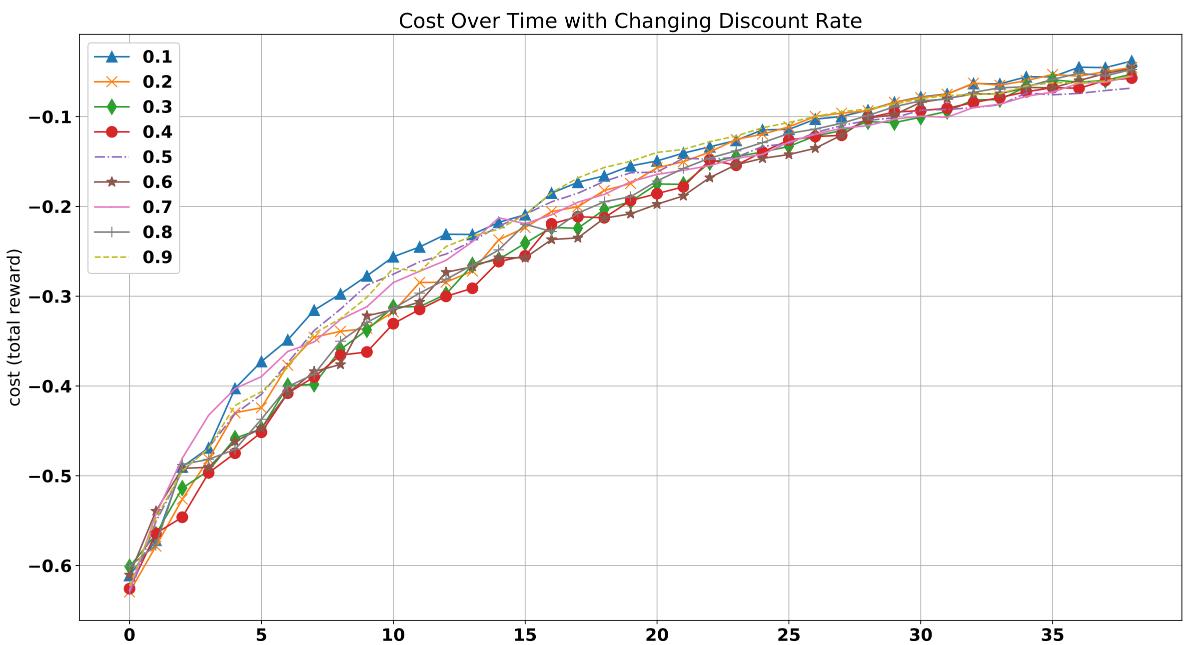


Figure 5.3: Simulation Results of Grid Search for The Discount Rate (γ), using Simple Dyad Model

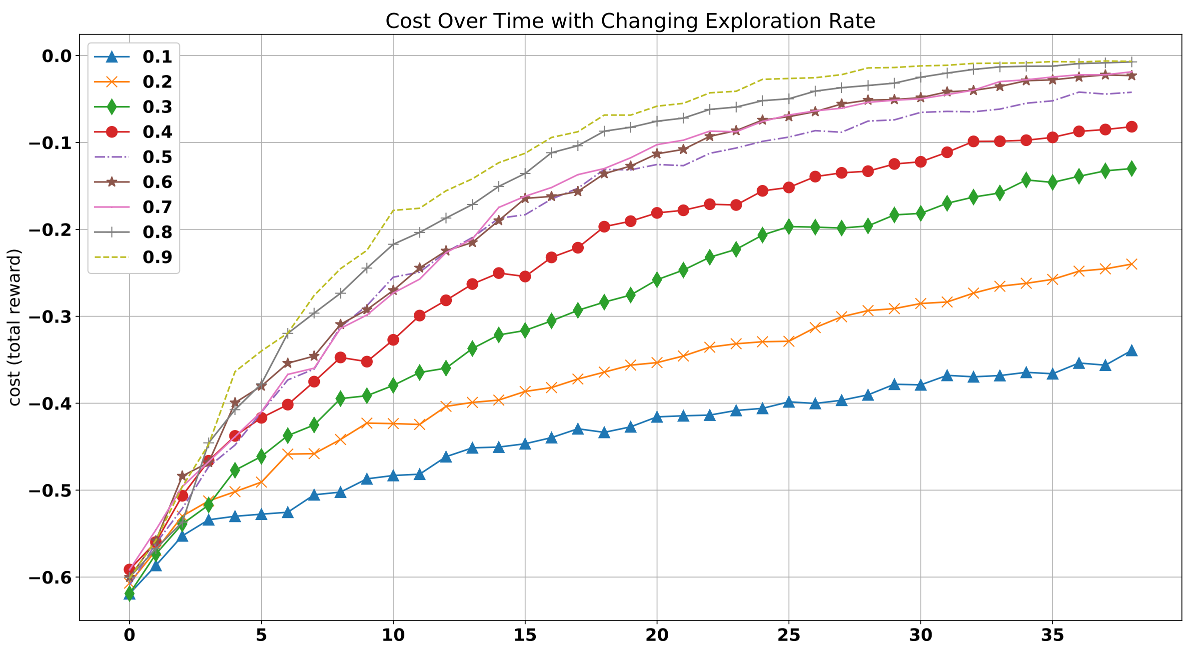


Figure 5.4: Simulation Results of Grid Search for The Exploration Rate (ϵ) with Q-table initialized at 0, using Simple Dyad Model

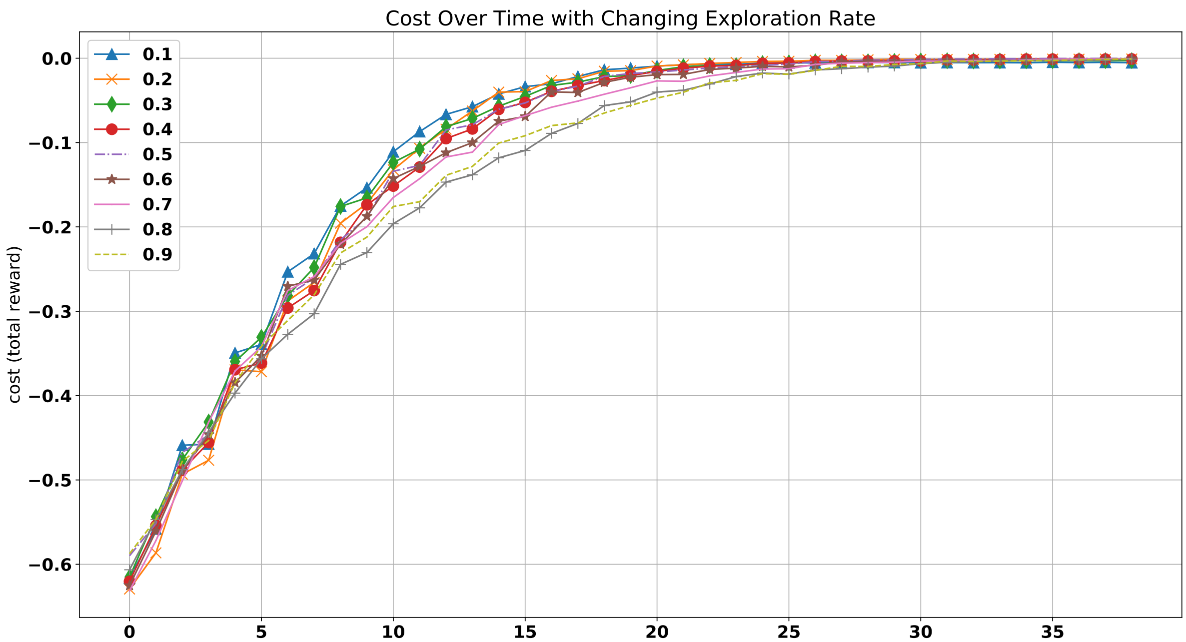


Figure 5.5: Simulation Results of Grid Search for The Exploration Rate (ϵ) with Q-table initialized at random, using Simple Dyad Model

encourage exploration, the performance improves and the exploration rate doesn't affect the performance of the algorithm as much. This can be seen by comparing Figure 5.4 (Q-Table is initialized with -100) and Figure 5.5. Similar to Figure 5.5, in the user study, the Q-table was initialized by positive values between 0 and 0.5 at random while the best possible value for the cost is 0.

The simple dyad model assumes that the voice activity of participants monotonically increases except when the noise has a negative value or decays after each round. This creates a dependency between the voice activity at different time intervals. Based on the real experiments, how much the participants talked in a 10-second interval was not dependent on how much they talked in the last one and the voice activity of a participant could go to 0 suddenly, for example, if they were typing in that 10-second interval. The second limitation of this model is the 5-seconds upper limit for each participant. This limit is not realistic, one participant could spend 0 seconds talking in an interval while the other participant will talk all of the 10 seconds in the measurement interval.

Independent Dyad Model: To address the limitations of the simple dyad model, we can assume participants' voice activity is unrelated to how much each participant talked previously, therefore the voice activity of the first participant is a random value between 0 and 10 seconds (which we call the initial estimate), and the second participant is 0 to 10 minus the initial estimate of the first participant, which also addresses the second limitation of the simple dyad model. The model is described in Algorithm 3. After the initial estimate value is generated, voice activity will either be equal to the initial estimate or 0 based on the action selected by the adaptive learning algorithm. If the algorithm only encouraged participant #1 then the value of voice activity for participant #2 is set to 0. To make the voice activity response to each action more realistic, we added a few possible scenarios in response to each. If the algorithm does nothing or says something that is not encouraging group work, there is a probability of 0.1 that the voice activity for both participants is equal to their initial estimate instead of 0. If the algorithm encourages participant #1 to speak, there is a 0.1 probability participant #2 also speaks, therefore their voice activity equal to their initial estimate instead of 0. If the robot encourages both participants, with a probability of 0.8 both of their voice activity is equal to their initial estimate, otherwise, with 0.2 probability only one of the participants has a voice activity equal to their initial estimate (0.1 probability participant #1 is 0, 0.1 probability participant #2 is 0). Figure 5.6 shows the performance of the algorithm is stable using this model. As expected, there is significant noise due to the randomness of the user model, however on average, the cost lowers overtime. Figure 5.7 and Figure 5.8 also show the talking time of both participants and their ratio, which we see mostly remain unchanged, with the ratio slightly improving

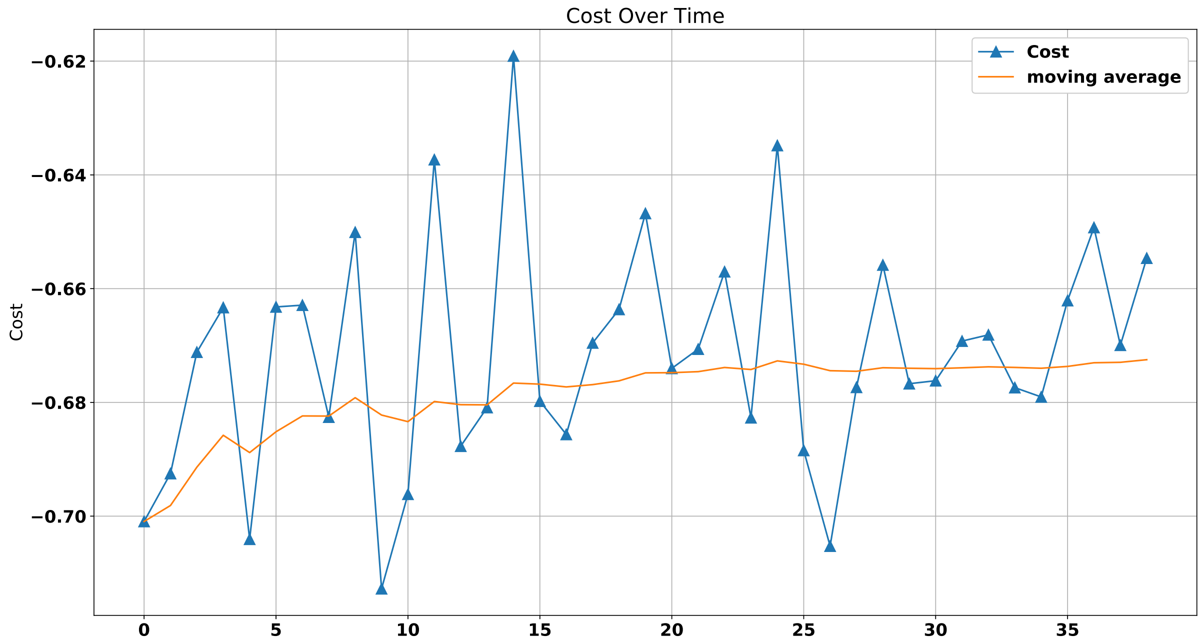


Figure 5.6: Simulation Results: Cost of Adaptive Learning Algorithm, using Independent Dyad Model

over time.

5.2.1 Lessons Learned

The simulation results show that the adaptive algorithm is not sensitive to the hyper-parameters when the Q-table is initialized at random. For the final user study, the learning rate for Q-Learning (λ) was set to 0.6 based on simulation results (Figure 5.2). The values of the discount rate (γ) and exploration rate (ϵ) were also selected based on simulation results. The value of the discount rate controls how much current audio input matters versus how much the next audio inputs will matter, set to 0.2 (Figure 5.3). The exploration rate, ϵ, was chosen to be 0.5 (Figure 5.4).

Algorithm 3 Independent Dyad Model

Require: $action_{t-1}, round$
  $decay \leftarrow 0.01 * round$
  $estimate_1 \leftarrow random(0\ to\ 10 - decay)$
  $estimate_2 \leftarrow random(0\ to\ 10 - decay)$
  $noise_1 \leftarrow random(-1\ to\ 1)$
  $noise_2 \leftarrow random(-1\ to\ 1)$
  $probability \leftarrow random(0\ to\ 1)$
  if $action_{t-1}\ = encouraging\ speaker\ 1$ **then**
    $speaker1_t \leftarrow estimate_1 + noise_1$
    if $probability < 0.1$ **then**
      $speaker2_t \leftarrow estimate_2 + noise_2$
    end if
  else if $action_{t-1} = encouraging\ speaker\ 2$ **then**
    $speaker2_t \leftarrow estimate_2 + noise_2$
    if $probability < 0.1$ **then**
      $speaker1_t \leftarrow estimate_1 + noise_1$
    end if
  else if $action_{t-1} = encouraging\ both\ speakers$ **then**
    if $probability < 0.8$ **then**
      $speaker1_t \leftarrow estimate_1 + noise_1$
      $speaker2_t \leftarrow estimate_2 + noise_2$
    else if $probability < 0.9$ **then**
      $speaker1_t \leftarrow estimate_1 + noise_1$
    else if $probability > 0.9$ **then**
      $speaker2_t \leftarrow estimate_2 + noise_2$
    end if
  else if $action_{t-1} = encouraging\ none$ OR $action_{t-1} = nothing$ **then**
    if $probability < 0.1$ **then**
      $speaker1_t \leftarrow estimate_1 + noise_1$
      $speaker2_t \leftarrow estimate_2 + noise_2$
    end if
  end if
  return $speaker1_t, speaker2_t$

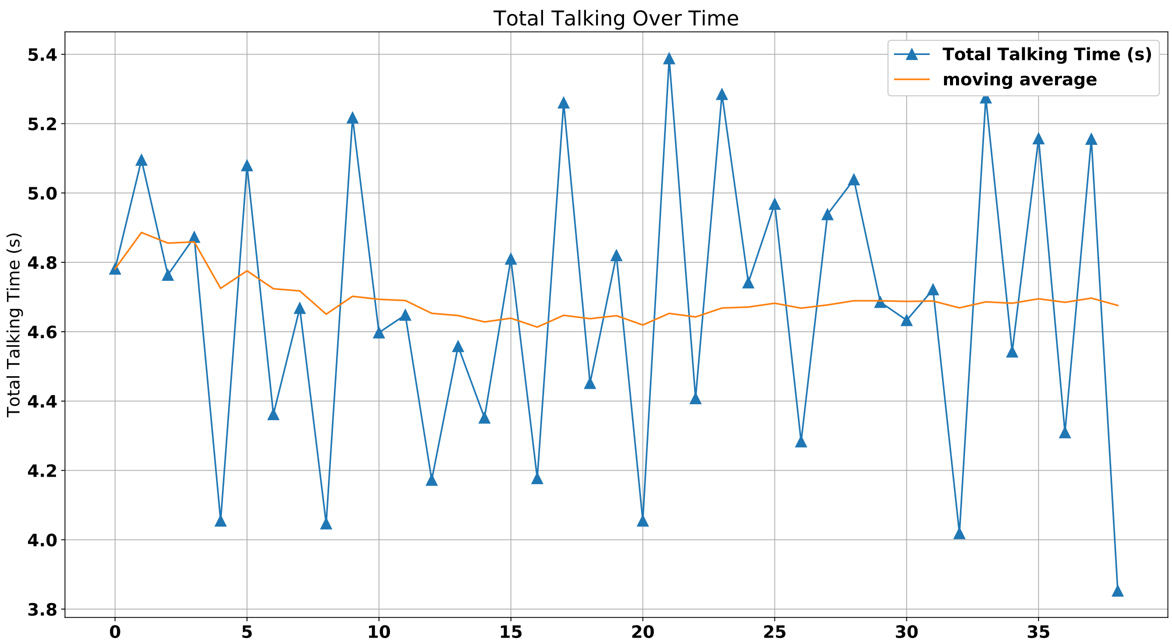


Figure 5.7: Simulation Results: Sum of Talking Time of Participant 1 and Participant 2, using Independent Dyad Model

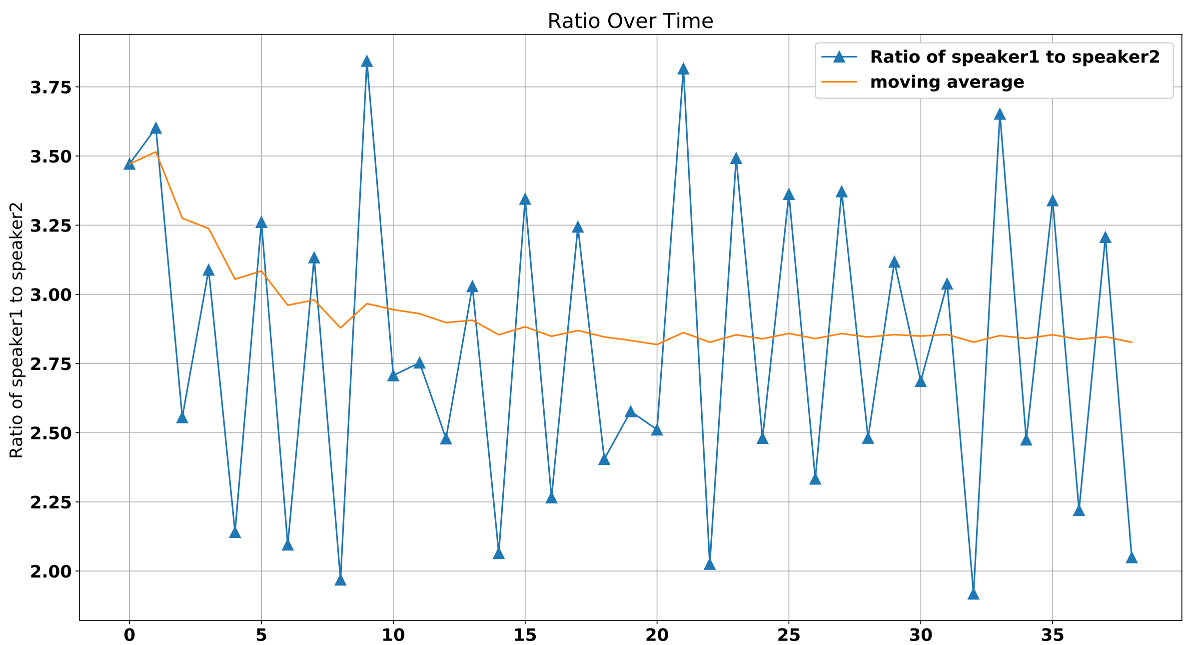


Figure 5.8: Simulation Results: Ratio for Talking Time of Participant 1 to Talking Time of Participant 2, using Independent Dyad Model

Chapter 6

Adaptive Teachable Robot User Study[1]

The goal of the experiment is to study the effect of adaptive social engagement encouragement on social engagement, task engagement, enjoyment and learning. This chapter discusses the experimental design, the recruitment and demographics of participants, the metrics and measures used, and finally the results of the user study.

6.1 Experimental Design

To study the effects of teamwork and how the robot can encourage teamwork, our user studies are done in dyads (two participants). A dyad is a special form of a group, research in psychology highlights the difference between the relationships formed in a dyad versus in a group [15, 53]. However, there is also research in psychology showing the results from dyadic studies could be scaled to larger groups [74, 81]. The curiosity of the robot, its learning speed, emotions and the questions it asked were kept constant across all the studies. The experiments were carried out between subject and in two conditions, baseline or adaptive. In the baseline condition, the robot does not encourage teamwork. In the adaptive condition, the robot encourages teamwork based on the audio input from the users. The user study was initially scheduled to be run in a physical school setting; however, due

[1] Results discussed in this Chapter have been submitted to the IEEE Conference on Robotics and Automation (*Effects of an Adaptive Teachable Robot Encouraging Teamwork on Students' Learning Process*, Baghaei Ravari, Lee, Law, Kulić)

to Covid-19 restrictions, the study was modified to be conducted remotely with 34 pairs of adult participants. The teaching/learning material was unmodified as the task of rock classification and the twelve rock articles were unfamiliar to most adults. A geologist at the University of Waterloo provided consulting during the material development phase. However, in the future, the material should be more carefully adjusted to different age groups [9, 47].

6.2 Participants

The user study was reviewed and received ethics clearance through the University of Waterloo Research Ethics Committee (ORE#40392). The participants were recruited through emails from the University of Waterloo and the social networks of the researchers. They were asked to sign up for a time slot, so they were randomly matched with other participants that signed up for the same time slot, except three pairs who knew each other and chose to sign up for the same time slot. After signing up, the participants received instructions to join a Zoom call. A total of 68 participants were recruited for this study, forming 34 dyads. However, two dyads were excluded from analysis due to system lags and errors, whereas two more dyads were excluded due to one of the participants arriving significantly later than the scheduled time. Two more dyads were excluded after analyzing the data for technical issues and missing data. Of the remaining dyads, 15 dyads were randomly assigned to the adaptive condition, and 13 dyads were assigned to the baseline (non-encouraging) condition. The participants were all adults between ages 20 to 35. Table 6.1 summarizes the dyad-wise demographics. The individual demographics are not relevant to our analysis as they are done with dyad units(a pair of participants), however, Table 6.2 summarizes the individual statistics of participants to give you a general overview of our participants. Additional information about the participants was capture through pre-study surveys (explained in Section 6.4) are stated in Appendix A and are similar for the participants in both conditions.

6.3 Procedure

On the scheduled date and time, Gamma (the humanoid robot) and the researcher were both in the Zoom call (Figure 6.1) waiting for the participants. The experimental condition was assigned beforehand, and the participants were not aware of the condition assigned. Participants were given their login credentials for the Curiosity Notebook after they joined

Table 6.1: Dyad-wise Demographics and Measurements

	Adaptive (n = 15)	Baseline (n = 13)	p-value
gender combinations	MM=2, FF=5 Mix = 8	MM=2, FF=4 Mix = 7	$\chi^2 \approx 0.14$ p=0.98
age difference (years)	4.13($\pm$3.38)	3.46($\pm$3.13)	t = 0.54, p= 0.6
dyad age sum (years)	51.47($\pm$4.6)	52.23($\pm$5.33)	t = -0.40, p = 0.69
started speaking English	11.8($\pm$9.21)	12.92($\pm$10.2)	t=-0.31 p=0.76
prior knowledge on topic	4.27, SD=1.22	6, SD=2	t=-2.81, p=0.01

Table 6.2: Mean demographics and measurements between conditions

	Adaptive (n = 30)	Baseline (n = 26)	p-value
age (years)	25.73($\pm$3.50)	26.12($\pm$3.50)	t=-0.25 p=0.8
gender (m/f)	W=18, M=12	W=15, M=11	$\chi^2 \approx 10^{-31}$ p=1
major	4 non-stem	4-non-stem	$\chi^2 \approx 0$ p=1
native English-speaker	No=15, Yes=15	No=18, Yes=8	$\chi^2 = 1.41$ p=0.24
started speaking English	5.9($\pm$7.76)	6.46($\pm$6.09)	t =-0.3,p=0.77
prior knowledge on topic	2.13, SD=0.9	3, SD=1.5	t = -2.67, p = 0.01

the call. All usernames were the preferred first name of the participants and it was the name Gamma used to address them. Upon logging-in, they had to sign the consent form, after which they proceeded to fill in the pre-study surveys (described in the next section 6.4 Measures). After the pre-study survey, the participants watched a three-minute instruction video, in which they learned about the Curiosity Notebook buttons and how to teach Gamma. After the video, participants arrived at the teaching interface, they were asked to wait for their partners to also finish all the previous steps. Before they started teaching, they were offered the chance to ask clarification questions from the researcher, as no questions would be answered during the teaching period. The participants' audio was recorded throughout the experiment. The duration of the experiment was up to the participants and it varied between 25 minutes and 69 minutes. After deciding to stop teaching Gamma, the participants were taken to the post-study questionnaires.

Figure 6.1: Zoom Call Interface, with two participants and Gamma

6.4 Measures

The pre-study surveys included demographics, familiarity and interest in robots, conversational agents and the topic of rock classification. They also included questions regarding the participant's interest in group work, and whether they knew their co-participant (group familiarity). The group familiarity survey was designed to measure some of the group characteristics that influence group work [33, 37]. In this study, the task was identical for all the participants, with no roles assigned, and no participant having prior experience with the system, therefore the focus was on group familiarity. We asked about the participants' familiarity with their co-participants in the study, both at an in-class and outside-class interaction level, and their interest in group work, both measured on a 4-point Likert scale to be consistent with the scale of the other questions in the familiarity survey. The 4-point Likert scales (odd-scaled) eliminate the neutral option, forcing the participants to lean toward either positive or negative responses [16], therefore it was deemed appropriate for this survey. Participants also answered a questionnaire on their feelings towards, and perception of Gamma (Godspeed Questionnaire [4]), in addition to their mood (Pick-A-Mood survey [21]). The last pre-study questionnaire was a knowledge test on rocks.

Post-study surveys included a questionnaire on the participants' experience. The participants answered questions on how much they enjoyed their experience, their interest in participating again, learning more about the topic they taught, and how much they enjoyed working with their partner. They were asked if they thought the robot was giving both of the participants a fair chance and encouraging group work. Other post-study surveys include another questionnaire on participants' perception of Gamma, another knowledge test, their motivation behind task completion (Intrinsic Motivation Inventory (IMI) [20] and Types of Motivation [27]).

6.5 Results

The results directly related to our hypothesis (as stated in Section 4.5), such as the time participants spent talking and the comparison between each participant's activity are elaborated upon in this section. Furthermore, we discuss the effects of group engagement on task engagement, enjoyment and learning gains. All the other data was captured prior to the experiment and after the study with surveys were examined, and we report no significant difference between the two conditions. All supplementary results from surveys are detailed in Appendix A.

6.5.1 Talking Duration

As the participants decided themselves when to end the experiment, talking time is normalised by the experiment's overall duration. Figure 6.2 shows the normalised talking time for both conditions. The average ratio of talking time to total experiment time was significantly larger for dyads in the adaptive condition, confirming H1 ($t(26) = 2.24$, $p = 0.03$). There was no statistically significant difference in overall experiment duration between the two conditions ($M_{adapt} = 2539(s)$, $SD = 511.8$, $M_{base} = 2684.39(s)$, $SD = 622.69$, $t(26) = -0.66$, $p = 0.51$).

The ratio of talking time to total time also depended on the gender (highest when both group members were female $\beta = 0.13$, $t(17) = 2.46$, $p = 0.03$), and the group's interest in conversational agents ($\beta = 0.03$, $t(17) = 2.2$, $p = 0.04$), which are both stronger than the correlation with the experimental condition ($\beta_{base} = -0.1$, $t(17) = -2.09$, $p = 0.05$).

The dyads in the adaptive condition also spend more time talking between 20 to 30 minutes into the teaching interaction, which could show that the adaptive encouragement of group collaboration helped in maintaining higher levels of communications in compassion to the baseline condition ($M_{adapt} = 163.7, SD = 91.12$ and $M_{base} = 148.27, SD = 62.59$, $t(26) = 2.88$, $p = 0.008$).

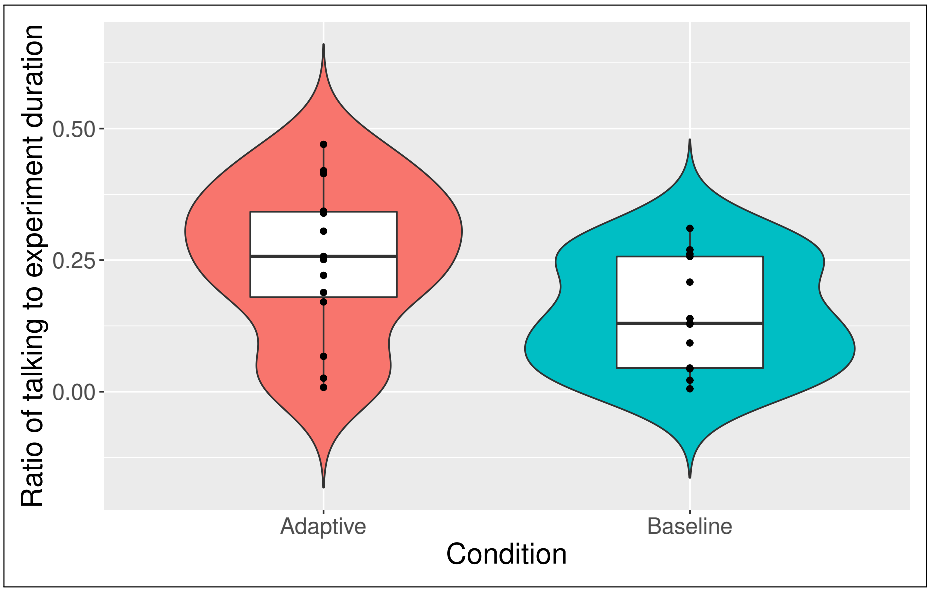


Figure 6.2: Average Normalized Overall Talking Time

6.5.2 Talking Trend

To analyze the effect of the encouragement over time, we can compare the trends of talking time between two conditions, shown in Figure 6.3. The adaptive condition results in higher talking time on average for the duration, but the trend is downward for both conditions and the slopes are not significantly different ($M_{adapt} = -0.81, SD = 0.75$ and $M_{base} = -0.72, SD = 1.27$, $t(26) = -0.23$, $p = 0.82$). Qualitatively, the initial conversations were mostly questions on how the system works or wondering about the functionality of different buttons, regardless of the condition. Those types of conversations faded as the participants learned how to use the system.

6.5.3 Relative Participation

We hypothesized that the adaptive condition would result in a more equal division of speaking between participants (H3). To investigate our hypothesis, we define the speaking percentage of each user at any given period by the ratio of their speaking activity duration to the overall speaking activity in that period. The ideal value of speaking percentage is 50%, which means both group members contributed equally to the conversation. Figure 6.4 illustrates how much the speaking percentage of one participant (in each dyad)

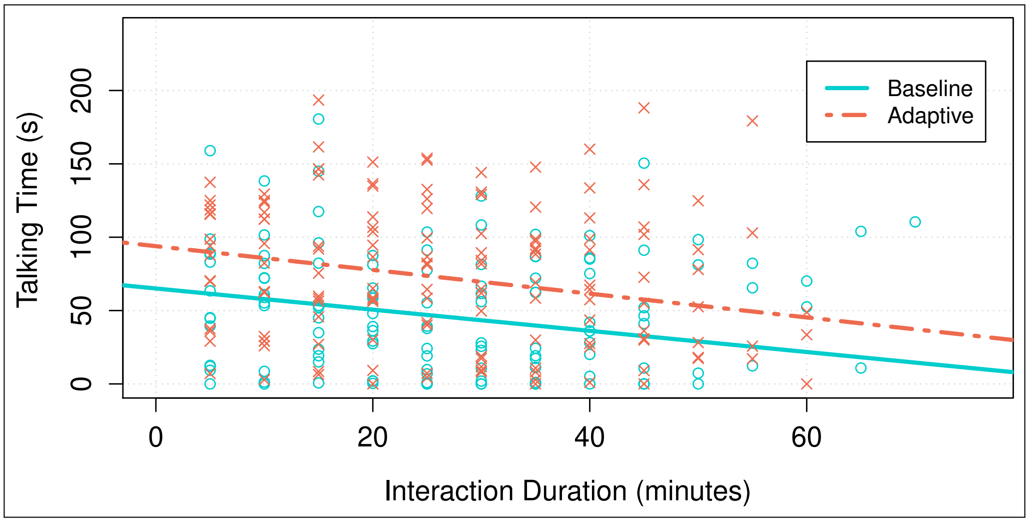


Figure 6.3: Slope of Talking Time

deviates from the 50% (calculated in (6.1)), where a lower deviation indicates more equal contribution. As shown in Figure 6.4, the average percentage difference is higher in the adaptive condition at the start, but it moves toward 0. In the baseline condition, however, the difference starts at a more desirable value but remains nearly constant, showing that the robot does not influence the balance between the two participants in the baseline condition. In the adaptive condition the slope is $M = -0.13$, $SD = 0.25$ while in the baseline condition slope is $M = -0.002$, $SD = 0.17$. The difference in slope is not statistically significant with $t(26) = -1.55$, $p = 0.13$.

$$\|100 \times \frac{(spk_1)}{(spk_1 + spk2)} - 0.5\| \tag{6.1}$$

6.5.4 Other Effects of the Experimental Condition

Task engagement, defined as the number of interactions participants had with the Curiosity Notebook, was higher in the adaptive condition. The number of buttons participants clicked ($F(1, 20) = 4.79$, $p = 0.04$), how many times they taught something ($F(1, 26) = 3.09$, $p = 0.06$), and how many articles they clicked ($F(1, 25) = 8.15$, $p = 0.01$) all are greater in the adaptive condition. The number of articles clicked was also correlated to participants' self-declared desire to teach (from the pre-study questionnaire) ($F(1, 25) = 6.29$, $p = 0.02$).

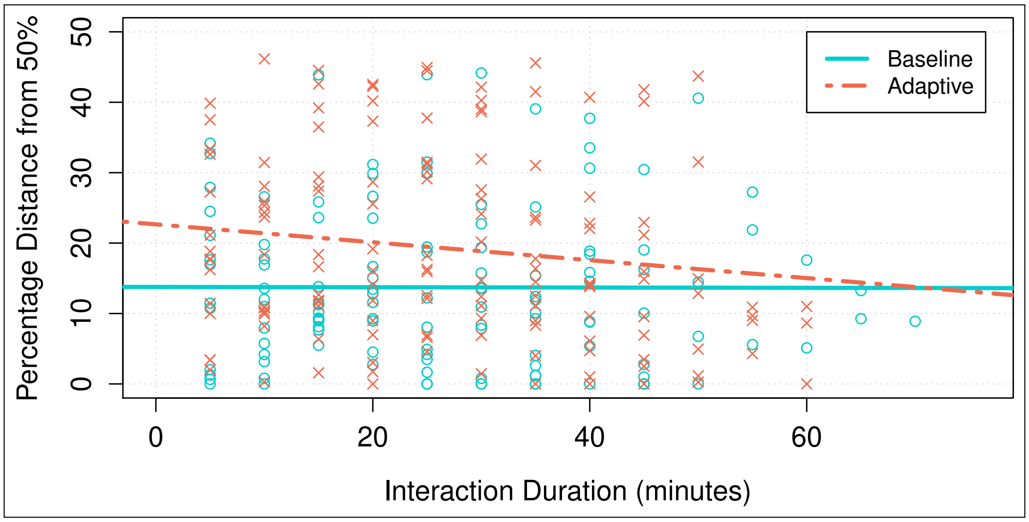


Figure 6.4: Distance (6.1) of Participants' Speaking Percentage from 50%

To compare learning gains, we have to consider that despite the random assignment, the participants in the baseline condition reported higher knowledge about rocks (refer to Table 6.1). To evaluate if there was any learning gain, we compared the score improvement (pre-score - post-score). The difference in learning gain between conditions was not significant, shown in Figure 6.5 (M_{adapt} = 1.74, SD = 3.47 , M_{base} = 2.38, SD = 2.53 , $t(23) = -0.56$, $p = 0.58$). The improvement in the score was highly and negatively correlated with the pre-study test score($\beta = -0.76$, $t(23) = -6.29$, $p = 0$), which means the participants with less knowledge showed higher learning gains. Secondly, as expected, the improvement was positively correlated with participants' interest in rocks ($\beta = 0.37$, $t(23) = 2.62$, $p = 0.02$). There was a weaker negative correlation between how much the participants thought they knew about rocks and their score improvement ($\beta = -0.4$, $t(23) = -1.71$, $p = 0.1$). Regardless of condition, the average knowledge test score improved after the study by 1 point.

Examining our second hypothesis (H2b) on increased dyad enjoyment (how much the participants enjoyed working with their partner), we report no significant difference between the conditions.

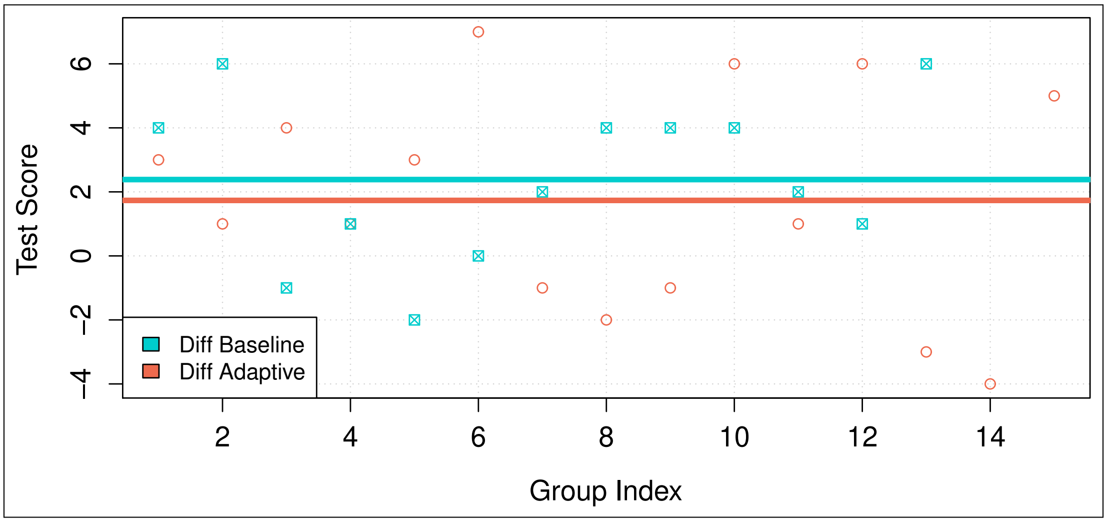


Figure 6.5: Knowledge Test Improvement in Both Conditions

6.5.5 Participants' Perception of the Robot and Qualitative Data

Qualitative results are captured through 2 different methods, survey and audio coding. Survey questions were the same for all participants, however, some questions were open ended, for example, a yes/no question such as "Do you think the robot was encouraging teamwork?" was followed by "Please explain why". The survey also included open ended questions on what the participants would like to change or any other feedback/comment they have. The second part of the qualitative data comes from the participants' conversation through the study, for example, "Gamma's laugh is funny".

Post-Study Survey

From the post-study Godspeed questionnaire, one characteristic of the robot differed significantly between the two conditions. The participants in the adaptive condition found Gamma less pleasant (sum of the dyad's perception on a 5-point Likert scale), and this is affected by both the experimental condition and their interest in rocks ($M_{adapt} = 7.47$, $SD =$ 1.36 and $M_{base} = 8.46$, $SD = 0.88$, $p = 0.03$). For the other Godspeed measures, despite the online user study and users only observing a video of the physical robot, they reacted positively to the humanoid robot. The users also anthropomorphised the robot during the teaching by commenting on its laugh, looks and intelligence. The rest of the results from the Godspeed questionnaire are documented in Appendix A.

From the post-study experience survey (section 6.4), most participants in both conditions considered the robot to be fair, in the baseline condition this was due to the turn-taking mechanism, and how the robot gave both participants their turns ($M_{adapt} = 1.93$, $SD = 0.26$ and $M_{base} = 1.58$, $SD = 0.79$, $t(25) = 3.13$, $p = 0.11$). In the adaptive condition, prompts for discussion among group members were considered a sign of fairness in 8 instances. For example, one participant wrote "it was fair because he told my partner to explain himself more". In the adaptive condition, there was one instance of the robot being deemed as unfair, because it kept interrupting the participant's ongoing discussion with its next prompts. In the baseline condition, 5 participants thought the robot was not fair, 2 of which were due to the robot interrupting them. Turn-taking and instance of the robot talking over participants are some of the current challenges of human-robot-collaboration and many of the cues used in face-to-face interaction were not applicable in the virtual setting of our experiment [2].

When it comes to participants' perception of whether the robot was encouraging of teamwork, the participants in the adaptive condition found the robot more encouraging ($M_{adapt} = 1.93$,$SD = 0.28$ and $M_{base} = 1.33$, $SD = 0.65$, $t(24) = 3.13$, $p = 0.004$) in the survey. Students in the adaptive condition found the statements robots said to be encouraging of teamwork in 27 instances. Only 2 students in the adaptive condition perceived the robot as not encouraging, the participants knew each other well before the experiment, they could have collaborated without any encouragement from the robot and hence didn't recognize the encouragement. Participants in the baseline condition interpreted forced turn-taking as encouragement of teamwork in 6 instances, while others cited unrelated reasons, such as the experiment being fun, or the need to figure out how the system works initially. 9 participants in the baseline condition stated the robot was not encouraging teamwork.

Results from the survey about the teaching experience and mood show that the majority (37) of participants in both conditions enjoyed their teaching experience ($M_{adapt} = 2.9$, $SD = 0.9$ and $M_{base} = 2.8$, $SD = 1$, on a 4 point Likert scale). In both conditions, the most frequently mentioned reason for enjoyment was that it was an "exciting experience". Some characteristics of voice and appearance of the humanoid robot (Gamma) were mentioned in the participants' elaboration, such as "enthusiastic robot", "fun movements", "sense of wonder in Gamma's face", in addition to some non-physical characteristics such as "good notes" and "fast learner". In both conditions, "slow" and "repetitive prompts" were the most common reason behind participants' dissatisfaction.

There is little difference between the two conditions in terms of the participants' perception of their teaching level, or whether they thought of Gamma as a good student. The encouragement of collaboration was mentioned as a characteristic by one participant in

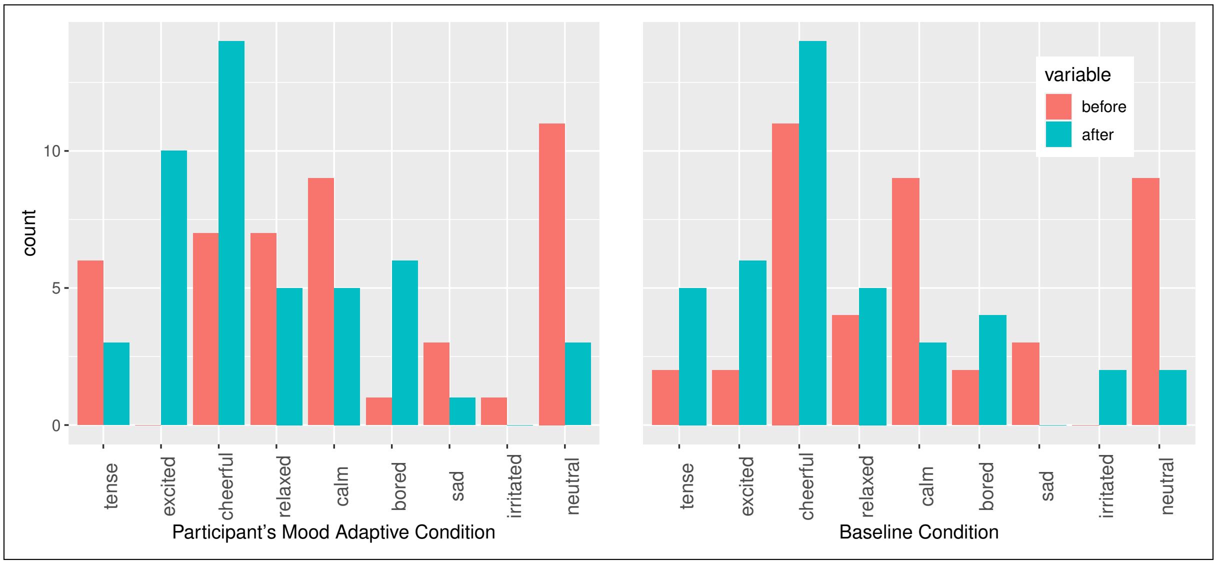


Figure 6.6: Participants' Mood Before and After the Experiment

the adaptive condition. A participant in the baseline condition called the robot socially unaware and "as if there were no humans in the interaction".

The results from the Pick-A-Mood scale [21] shows the 20% of participants in the adaptive condition felt tense before the experiment (as seen in Figure 6.6), and the numbers dropped to 10% after the experiment. However, in the baseline condition feeling tense increased from 8% before the experiment to 19% afterward. Feeling excited went from 0% to 33% in the adaptive condition and 8 to 23% in the baseline condition. Lastly, more participants in the adaptive condition thought Gamma was excited (83%) in comparison to the baseline (53%) as seen in Figure 6.7.

In participants' general feedback on what they wanted to change, recurring requests were to make the interaction faster, make the Curiosity Notebook easier to interact with, and allow participants more freedom or give them more options. Feedback related to changes in the robot were similar in both conditions, mostly to tone down the excitement, especially laughing. There were also a few reports of Gamma being hard to hear over the call or the voice getting interrupted.

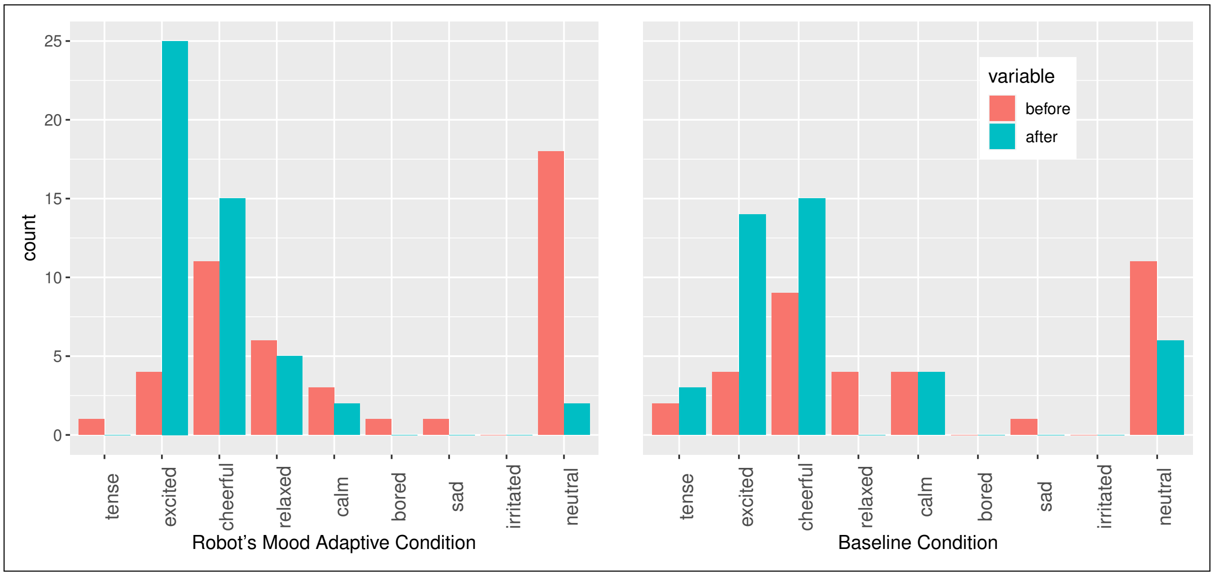


Figure 6.7: Perception of Robot's Mood Before and After the Experiment

Participants' Audio Recordings

The conversations between the participants were coded in 10 different categories, 12 sessions were randomly selected to be coded. The categories are summarized in Table 6.3. Short term plans for teaching can happen in every step of the teaching and included letting the other participant know of the chosen rock or sentence or the immediate next action. Short term plans only happened in the adaptive condition as they were reactions to encouraging statements by the robot. However, in the adaptive condition, participants showed the habit of discussing short term plans after a few times of being encouraged to do so, even when the robot didn't use an encouraging statement. Despite the lack of robot encouragement in the baseline condition, there was still some planning and collaboration between the participants (in 5 out of 6 sessions). Some participants (2 sessions) in the baseline condition chose to discuss long term plans on how they will approach teaching before they start, for example, "You can teach first", "I think we should first teach all igneous rocks", or "We should describe all of them first and then compare". One dyad in the baseline condition asked before the study if they are allowed to talk to each other before they start so they can come up with a strategy. Long-term plans involved general statements, as opposed to short-term plans, which include the immediate action the user is intending to take. In the baseline condition, sometimes one participant would ask a question (e.g. "What rock did you pick") that would be similar to a short term plan, or a participant would suggest an action for the other (e.g. "You should teach Garbbro now") but these scenarios didn't present the same opportunity for discussion or collaboration as the robot's explicit encouragement did. In 2 instances in the adaptive condition, one participant's comment or question was ignored by the other participant, resulting in termination of all further communications. In 2 instances (in the baseline condition), one user dominated the conversation and made most of the teaching decisions. Three dyads in the adaptive condition showed curiosity about what if they teach something wrong or spell wrong. In 2 of the dyads that didn't create any conversation, all four participants struggled to learn how to work with the Curiosity Notebook but that wasn't enough for them to start talking to their group-mate. Generally, for the participants who had a hard time figuring out how to work with the Curiosity Notebook (3 instances, 1 in the adaptive condition) their experience was negatively affected and one participant of a dyad in the adaptive condition expressed signs of frustration during the experiment such saying "I hate this robot". It appears that students who communicated for longer (most of them in the adaptive condition) felt more comfortable sharing their opinions such as comments on Gamma ("It's such a cute robot"), comments on articles ("didn't know this about slate") and the experience with their group-mates. All but one of the dyads discussed when it came to ending the experiment.

6.5.6 Q-Learning Results

As discussed in Chapter 4, the exploration rate of the algorithm was set to 0.5, this means that 50% of the time the robot would select a response according to the maximum value of the Q-table and the other 50% of the time, it would select a random response. In 12 of the 15 groups in the adaptive condition, on average, the adaptive choice performed better (led to better reward) in comparison to the random choice. However, the difference between the average reward resulting from the two types of choice was not significantly different. To further study the significance of the adaptive condition, the experiment should include an additional condition (besides adaptive and baseline) in which the robot randomly encourages the participants to collaborate. Additionally, the adaptive condition and the random condition could become more distinct if the robot is given more freedom in its behaviour, and has a bigger action repertoire. The action repertoire limitations are discussed in more detail in the next chapter (Chapter 7).

Table 6.3: Teaching Session Audio Coding

Category	**Meaning**	**Example**
teaching plans - long term	Overall plans for how to proceed with the teaching	"I think we're not teaching enough sentences"
teaching plans - short term	Discussions around the next action	"obsidian, I wanted to describe obsidian"
Questions about Interface	How and why questions about the interface	"Oh is it my turn now?"
Discussion on articles	Discussing the information read in any of articles	"It says Quartz can have different colours depending on the beach location"
Comments on Gamma	Comments about robot's behaviour	"why is he sneezing? bless you"
Comments on teaching	Giving feedback on teaching action of their teammate after the action	"I think he wanted a different sentence from the one you selected"
Unrelated	Comments that are not about the experiment or teaching	– didn't happen in any of the sessions –
Unanswered	Any of the above that goes unanswered by the other participant	– no acknowledgement or answer from their partner –
Ending	Conversations around when to end the teaching session	"should we finish now?"

6.6 Summary

We ran a user study (n = 68), where a pair of participants work together to teach a humanoid robot about rocks and minerals. The experiment was between subjects consisted of two conditions. In the adaptive condition, the robot uses reinforcement learning to maximise interaction between the students. In the baseline (control) condition the robot does not encourage group/social engagement. The studies were conducted online and on a Zoom call, with two participants, the humanoid robot Gamma, and the researcher.

The results of our user study confirmed our first hypothesis (**H1**), robot encouraging teamwork increased team communication. The results also show the potential for an adaptive encouraging robot to create more balanced participation between the group members however we can't confirm (**H3**) as the result is not statistically significant. The results were aligned with (**H2a**) as the participants in adaptive condition clicked on more articles, and thought more to the robot. The results, however, were not consistent with (**H2b**) and (**H2c**), as there was no significant difference in enjoyment and learning gain between the participants in the two conditions.

The participants in the adaptive condition also perceived the robot as more excited and reported feeling less tense after the experiment. They also recognized the robot was encouraging of teamwork. The participants of both conditions reported similar levels of enjoyment from the experiment and considered the robot to be fair. The most common feedback for improvement of the system was related to making the interaction faster and give users more flexibility in how they go teaching the robot.

Chapter 7

Conclusions

The results of our user study showed that encouraging group engagement increased communication as well as participants' task engagement and exploration. The results also show the potential for an adaptive encouraging robot to create more balanced participation between the group members. However, we were not able to show any effect of increased communication on learning outcomes. When it comes to participants' perception, they noticed the encouragement by the robot to collaborate (no significant difference between conditions) and they perceived the interaction as more fair in the adaptive condition.

7.1 Limitations and Future Work

Our study has several limitations. First, participants' group engagement was only measured through their verbal communication and didn't include factors such as emotions and non-verbal behaviour that could be measured in an in-person study. The communication was also not categorized based on the subject of discussion to differentiate between on-task and off-task communication. Work by Sinha et. al. [63] defined social engagement in groups involving two concepts, the first one was group cohesion, and the understanding that the task was a shared activity, and the second was equitable participation. In their study, social group engagement was measured from videotapes and offline. Some behaviours were marked as positive socio-emotional, such as respectfulness, cohesiveness, responsiveness, and some as negative socio-emotional behaviour such as attempts to dominate or ignoring and excluding other group members which resulted in lower social engagement scores. Future systems equipped with online speech recognition, facial expression recognition or audiovisual emotion recognition could categorize the group conversations and user's emotions as positive or negative socio-emotional behaviour. Including other measures of engagement will improve the adaptive learning algorithm by providing it with more accuracy and feedback (reward).

Secondly, the robot's action repertoire could be expanded by including other forms of encouragement, for example, non-verbal behaviours such as eye contact, or other verbal and non-verbal behaviours such as back-channelling. Back-channeling includes active listening techniques such as a glimpse, using expressions such as "hmm" or Chameleon effect which is when one interaction partner mimics the other [69].' Supporting the participants' answers and ideas has also been shown to increase group cohesion which could increase engagement [64]. The reinforcement learning algorithm used for adaptation could also be improved by using a dynamic/decaying learning rate [86], discount rate [55] and exploration rate [23,78].

There is a lack of long-term studies when it comes to social robots in education, even though they are necessary to show the feasibility of integrating robots into everyday life [18]. Performing a long-term study will allow for more accurate measurements of the learning gain, fosters stronger social bonds and interactions, and studies show it is possible to maintain long-term engagement [7, 18, 46]. At the same time, one of the challenges of introducing robots in education is the novelty effect (the initial high response to new technology). This issue could be addressed with long-term studies, which successfully maintained interest and engagement over long-term interaction [73] and some of the long-term studies have shown promising result despite the drop in interest [11, 12].

The suitability of the system for the tested age-group also needs to be further validated. It is not yet clear if the systems that are appropriate for children can be used for adults and most of the research in social robots for education involves children [7]. The existing studies with adults use different approaches from studies with children, making it difficult to compare the performance of teachable robots between age-groups [73]. Additionally, as discussed in Chapter 6, the learning materials themselves could be changed to more appropriate levels for different age groups.

Additionally, due to Covid-19 restrictions, our study was performed remotely, introducing the possibility of delays and poor quality audio/video that could have affected the engagement negatively. The experience of the users could be improved by integrating strong video streaming services into the Curiosity Notebook, reducing the probability of the users missing out on the humanoid robot's actions and behaviours. The results might differ for an in-person study. The participants also couldn't get the full benefits of physical robots such as their capability to display more social behaviours during the interaction and additional learning gains from interacting with robots with a physical embodiment [7].

However, the remote study approach could be deployed more broadly in future studies, given the emergence of online learning platforms.

One possible direction for feature work that could improve the results and study the effects of adaptability separate from the effects of group engagement, is to include a third experimental condition, in which the robot encourages group engagement but does so randomly without considerations for the current group engagement levels. Further, the adaptive algorithm could be expanded to include other forms of rewards such as task engagement. In that case, the robot will learn the best encouragement techniques for group engagement that lead to the highest task engagement (such as user responsiveness, completion time).

References

[1] Evinella Alexopoulou and Rosalind Driver. Small-group discussion in physics: Peer interaction modes in pairs and fours. *Journal of Research in Science Teaching*, 33(10):1099–1114, 1996.

[2] Sean Andrist, Dan Bohus, Bilge Mutlu, and David Schlangen. Turn-taking and coordination in human-machine interaction. *AI Magazine*, 37(4):5–6, Jan. 2017.

[3] Brenna D. Argall, Sonia Chernova, Manuela Veloso, and Brett Browning. A survey of robot learning from demonstration. *Robotics and Autonomous Systems*, 57(5):469 – 483, 2009.

[4] Christoph Bartneck, Elizabeth Croft, and Dana Kulic. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, 1(1):71–81, 2009.

[5] Paul Baxter, Emily Ashurst, Robin Read, James Kennedy, and Tony Belpaeme. Robot education peers in a situated primary school study: Personalisation promotes child learning. *PLOS ONE*, 12(5):1–23, 05 2017.

[6] Philip Beesley, Matthew Chan, Rob Gorbet, Dana Kulic, and Mo Memarian. Evolving systems within immersive architectural environments: New research by the living architecture systems group. *Next Generation Building*, 2(1):31–56, 2015.

[7] Tony Belpaeme, James Kennedy, Aditi Ramachandran, Brian Scassellati, and Fumihide Tanaka. Social robots for education: A review. *Science Robotics*, 3(21), Aug 2018.

[8] Cynthia Breazeal. *Designing Sociable Robots*. MIT Press, Cambridge, MA, USA, 2002.

[9] Gina N. Cervetti, Elfrieda H. Hiebert, P. David Pearson, and Nicola A. McClung. Factors that influence the difficulty of science words. *Journal of Literacy Research*, 47(2):153–185, 2015.

[10] Tricia Chaffey, Hyeji Kim, Emilia Nobrega, Nichola Lubold, and Heather Pon-Barry. Dyadic stance in natural language communication with a teachable robot. In *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '18, pages 85–86, New York, NY, USA, 2018. ACM.

[11] Shruti Chandra, Raul Paradeda, Hang Yin, Pierre Dillenbourg, Rui Prada, and Ana Paiva. Affect of robot's competencies on children's perception. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems*, AAMAS '17, pages 1490–1492, Richland, SC, 2017. International Foundation for Autonomous Agents and Multiagent Systems.

[12] Shruti Chandra, Raul Paradeda, Hang Yin, Pierre Dillenbourg, Rui Prada, and Ana Paiva. Do children perceive whether a robotic peer is learning or not? In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '18, pages 41–49, New York, NY, USA, 2018. ACM.

[13] Vasiliki Charisi, Daniel Patrick Davison, Frances Martine Wijnen, Jan van der Meij, Dennis Reidsma, Tony Prescott, Wouter van Joolingen, and Vanessa Evers. Towards a child-robot symbiotic co-development: a theoretical approach. In M. Salem, A. Weiss, P. Baxter, and K. Dautenhahn, editors, *Proceedings of the Fourth International Symposium on "New Frontiers in Human-Robot Interaction"*, pages 331–336. The Society for the Study of Artificial Intelligence and Simulation of Behaviour (AISB), 4 2015. eemcs-eprint-26626.

[14] Catherine C. Chase, Doris B. Chin, Marily A. Oppezzo, and Daniel L. Schwartz. Teachable agents and the protégé effect: Increasing the effort towards learning. *Journal of Science Education and Technology*, 18(4):334–352, Aug 2009.

[15] Gus Cooney, Adam M Mastroianni, Nicole Abi-Esber, and Alison Wood Brooks. The many minds problem: disclosure in dyadic versus group conversation. *Current Opinion in Psychology*, 31:22 – 27, 2020. Privacy and Disclosure, Online and in Social Interactions.

[16] James T. Croasmun and L. Ostrom. Using likert-type scales in the social sciences. *Journal of Adult Education*, 40:19–22, 2011.

[17] Heriberto Cuayáhuitl. Robot learning from verbal interaction: A brief survey. In *AISB Convention 2015*. Society for the Study of Artificial Intelligence and the Simulation of Behaviour, 2015. AISB Convention 2015 ; Conference date: 20-04-2015 Through 22-04-2015.

[18] Daniel P. Davison, Frances M. Wijnen, Vicky Charisi, Jan van der Meij, Vanessa Evers, and Dennis Reidsma. Working with a social robot in school: A long-term real-world unsupervised deployment. In *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '20, page 63–72, New York, NY, USA, 2020. Association for Computing Machinery.

[19] Jan de Wit, Thorsten Schodde, Bram Willemsen, Kirsten Bergmann, Mirjam de Haas, Stefan Kopp, Emiel Krahmer, and Paul Vogt. The effect of a robot's gestures and adaptive tutoring on children's acquisition of second language vocabularies. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '18, page 50–58, New York, NY, USA, 2018. Association for Computing Machinery.

[20] Edward L. Deci, Haleh Eghrari, Brian C. Patrick, and Dean R. Leone. Facilitating internalization: The self-determination theory perspective. *Journal of personality*, 62 1:119–42, 1994.

[21] Pieter M.A. Desmet, Martijn H. Vastenburg, and Natalia Romero. Mood measurement with pick-a-mood: Review of current methods and design of a pictorial self-report scale. *Journal of Design Research*, 14(3):241–279, 2016.

[22] DK. *Nature Guide Rocks and Minerals: The World in Your Hands*. Dorling Kindersley Limited, 2012.

[23] Alexandre dos Santos Mignon and Ricardo Luis de Azevedo da Rocha. An adaptive implementation of epsilon-greedy in reinforcement learning. *Procedia Computer Science*, 109:1146 – 1151, 2017. 8th International Conference on Ambient Systems, Networks and Technologies, ANT-2017 and the 7th International Conference on Sustainable Energy Information Technology, SEIT 2017, 16-19 May 2017, Madeira, Portugal.

[24] Vikki Du Preez and Veronica Barnes. Encouraging engagement. In *Proceedings of the 2nd Conference on Design, Development and Research*, page 214. Design, Development & Research Conference- CPUT, 2012.

[25] Terrence Fong, Illah Nourbakhsh, and Kerstin Dautenhahn. A survey of socially interactive robots. *Robotics and Autonomous Systems*, 42(3):143 – 166, 2003.

[26] Robyn M. Gillies. Teachers' and students' verbal behaviours during cooperative and small-group learning. *British Journal of Educational Psychology*, 76(2):271–287, 2006.

[27] Frederic Guay, Robert Vallerand, and Céline Blanchard. On the assessment of situational intrinsic and extrinsic motivation: The situational motivation scale (sims). *Motivation and Emotion*, 24:175–213, 09 2000.

[28] N. Honovich. *Ultimate Explorer Field Guide: Rocks and Minerals.* National Geographic kids. National Geographic Society, 2016.

[29] Deanna Hood, Séverin Lemaignan, and Pierre Dillenbourg. When children teach a robot to write: An autonomous teachable humanoid which uses simulated handwriting. In *HRI '15: Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot*, HRI '15, page 83–90, New York, NY, USA, 2015. Association for Computing Machinery.

[30] Charles Lee Isbell, Jr. Christian, R. Shelton, Michael Kearns, Satinder Singh, and Peter Stone. A social reinforcement learning agent. In *In Proceedings of the Fifth International Conference on Autonomous Agents (Agents-01*, pages 377–384, 2001.

[31] Alexis Jacq, Séverin Lemaignan, Fernando Garcia, Pierre Dillenbourg, and Ana Paiva. Building successful long child-robot interactions in a learning context. *ACM/IEEE International Conference on Human-Robot Interaction*, 2016-April:239–246, 2016.

[32] Frank Jamet, Olivier Masson, Baptiste Jacquet, Jean-Louis Stilgenbauer, and Jean Baratgin. Learning by teaching with humanoid robot: A new powerful experimental tool to improve children's learning ability. *Journal of Robotics*, 2018:1–11, 2018.

[33] Jeroen Janssen, Gijsbert Erkens, Paul A. Kirschner, and Gellof Kanselaar. Influence of group member familiarity on online collaborative learning. *Computers in Human Behavior*, 25(1):161 – 170, 2009.

[34] Felix Jimenez, Tomohiro Yoshikawa, Takeshi Furuhashi, and Masayoshi Kanoh. Effects of a novel sympathy-expression method on collaborative learning among junior high school students and robots. *J. Robotics Mechatronics*, 30:282–291, 2018.

[35] Felix Jimenez, Tomohiro Yoshikawa, Takeshi Furuhashi, Masayoshi Kanoh, and Tsuyoshi Nakamura. Effects of collaborative learning between educational-support robots and children who potential symptoms of a development disability. In *2016 Joint 8th International Conference on Soft Computing and Intelligent Systems (SCIS) and*

17th International Symposium on Advanced Intelligent Systems (ISIS), pages 266–270, 2016.

[36] Wafa Johal, Alexis Jacq, Ana Paiva, and Pierre Dillenbourg. Child-robot spatial arrangement in a learning by teaching activity. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 533–538, Aug 2016.

[37] Dong I. Jung and John J. Sosik. Effects of group characteristics on work group performance: A longitudinal investigation. *Group Dynamics*, 3(4):279–290, December 1999.

[38] Takayuki Kanda, Takayuki Hirano, Daniel Eaton, and Hiroshi Ishiguro. Interactive robots as social partners and peer tutors for children: A field trial. *Hum.-Comput. Interact.*, 19(1):61–84, June 2004.

[39] James Kennedy, Paul Baxter, and Tony Belpaeme. Comparing Robot Embodiments in a Guided Discovery Learning Interaction with Children. *International Journal of Social Robotics*, 7(2):293–308, 2015.

[40] Jens Kober, J. Andrew Bagnell, and Jan Peters. Reinforcement learning in robotics: A survey. *Int. J. Rob. Res.*, 32(11):1238–1274, September 2013.

[41] Jacqueline Kory and Cynthia Breazeal. Storytelling with robots: Learning companions for preschool children's language development. In *The 23rd IEEE International Symposium on Robot and Human Interactive Communication*, pages 643–648, Aug 2014.

[42] Jacqueline Kory Westlund and Cynthia Breazeal. The interplay of robot language level with children's language learning during storytelling. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts*, HRI'15 Extended Abstracts, pages 65–66, New York, NY, USA, 2015. ACM.

[43] Kazumi Kumagai, Ikuo Mizuuchi, Lingheng Meng, Alexandru Blidaru, Philip Beesley, and Dana Kulić. Towards individualized affective human-machine interaction. In *2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 678–685, 2018.

[44] Edith Law, Parastoo Baghaei Ravari, Nalin Chhibber, Dana Kulic, Stephanie Lin, Kevin D. Pantasdo, Jessy Ceha, Sangho Suh, and Nicole Dillen. Curiosity notebook: A platform for learning by teaching conversational agents. In *Extended Abstracts of*

the 2020 CHI Conference on Human Factors in Computing Systems, CHI EA '20, page 1–9, New York, NY, USA, 2020. Association for Computing Machinery.

[45] Edith Law, Ken Jen Lee, and Parastoo Baghaei Ravari. The Curiosity Notebook: A Platform for SupportingLearning with Teachable Robots. In *HRI 2020 Workshop on Exploring Creative Contents in Social Robots*, 2020.

[46] Severin Lemaignan, Alexis Jacq, Deanna Hood, Fernando Garcia, Ana Paiva, and Pierre Dillenbourg. Learning by Teaching a Robot: The Case of Handwriting. *IEEE Robotics and Automation Magazine*, 23(2):56–66, 2016.

[47] Keith Lenz and Jean Schumaker. *Adapting Language Arts, Social Studies, and Science Materials for the Inclusive Classroom*, volume Vol. 3, Grades Six through Eight. ERIC Clearinghouse on Disabilities and Gifted Education, 2003.

[48] Markus Lindberg, Kristian Mansson, Birger Johansson, Agneta Gulz, and Christian Balkenius. Does a robot tutee increase children's engagement in a learning-by-teaching situation? In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 10498 LNAI, pages 243–246. Springer Verlag, 2017.

[49] Nichola Lubold, Erin Walker, and Heather Pon-Barry. Effects of voice-adaptation and social dialogue on perceptions of a robotic learning companion. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 255–262, March 2016.

[50] Mark J. Macgowan and Frederick L. Newman. Factor structure of the group engagement measure. *Social Work Research*, 29(2):107–118, 2005.

[51] Beth Maloch. Scaffolding student talk: One teacher's role in literature discussion groups. *Reading Research Quarterly*, 37(1):94–112, 2002.

[52] Lingheng Meng, Daiwei Lin, Adam Francey, Rob Gorbet, Philip Beesley, and Dana Kulic. Learning to engage with interactive systems: A field study. *CoRR*, abs/1904.06764, 2019.

[53] Jerry W. O'Dell. Group size and emotional interaction. *Journal of Personality and Social Psychology*, 8(1, Pt.1):75–78, 1968.

[54] Lena Pareto. Robot as tutee. In Munir Merdan, Wilfried Lepuschitz, Gottfried Koppensteiner, and Richard Balogh, editors, *Robotics in Education*, pages 271–277, Cham, 2017. Springer International Publishing.

[55] Silviu Pitis. Rethinking the discount factor in reinforcement learning: A decision theoretic approach, 2019.

[56] Aditi Ramachandran, Chien-Ming Huang, and Brian Scassellati. Give me a break! personalized timing strategies to promote learning in robot-child tutoring. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '17, page 146–155, New York, NY, USA, 2017. Association for Computing Machinery.

[57] Sally Roberts. Using practitioner research to investigate the role of the teacher in encouraging student interaction within group work. *Nurse Education Today*, 28(1):85 – 92, 2008.

[58] Ben Robins, Kerstin Dautenhahn, Rene Te Boekhorst, and Aude Billard. Robotic assistants in therapy and education of children with autism: Can a small humanoid robot help encourage social interaction skills? *Univers. Access Inf. Soc.*, 4(2):105–120, December 2005.

[59] Ognjen Rudovic, Jaeryoung Lee, Lea Mascarell-Maricic, Björn W. Schuller, and Rosalind W. Picard. Measuring engagement in robot-assisted autism therapy: A cross-cultural study. *Frontiers in Robotics and AI*, 4:36, 2017.

[60] Martin Saerbeck, Tom Schut, Christoph Bartneck, and Maddy Janse. Expressive robots in education - varying the degree of social supportive behavior of a robotic tutor. In *28th ACM Conference on Human Factors in Computing Systems (CHI2010)*, pages 1613–1622, Atlanta, 2010. ACM.

[61] Thorsten Schodde, Kirsten Bergmann, and Stefan Kopp. Adaptive robot language tutoring based on bayesian knowledge tracing and predictive decision-making. In *2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI*, pages 128–136, 2017.

[62] Kezang Sherab. Strategies for encouraging behavioural and cognitive engagement of pre-service student-teachers in bhutan: an action research case study. *Educational Action Research*, 21(2):164–184, 2013.

[63] Suparna Sinha, Toni Kempler Rogat, Karlyn R. Adams-Wiggins, and Cindy E. Hmelo-Silver. Collaborative group engagement in a computer-supported inquiry learning environment. *International Journal of Computer-Supported Collaborative Learning*, 10(3):273–307, Sep 2015.

[64] Sarah Strohkorb Sebo, Ling Liang Dong, Nicholas Chang, and Brian Scassellati. Strategies for the inclusion of human members within human-robot teams. In *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '20, page 309–317, New York, NY, USA, 2020. Association for Computing Machinery.

[65] Richard S.. Sutton and Andrew G.. Barto. *Reinforcement learning: an introduction.* The MIT Press., 2018.

[66] Fumihide Tanaka, Kyosuke Isshiki, Fumiki Takahashi, Manabu Uekusa, Rumiko Sei, and Kaname Hayashi. Pepper learns together with children: Development of an educational application. *IEEE-RAS International Conference on Humanoid Robots*, 2015-Decem:270–275, 2015.

[67] Fumihide Tanaka and Takeshi Kimura. The use of robots in early education: A scenario based on ethical consideration. In *RO-MAN 2009 - The 18th IEEE International Symposium on Robot and Human Interactive Communication*, pages 558–560, Sep. 2009.

[68] Fumihide Tanaka and Shizuko Matsuzoe. Children teach a care-receiving robot to promote their learning: Field experiments in a classroom for vocabulary learning. *J. Hum.-Robot Interact.*, 1(1):78–95, July 2012.

[69] Hamish Tennent, Solace Shen, and Malte Jung. Micbot: A peripheral robotic object to shape conversational dynamics and team performance. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 133–142, 2019.

[70] Andrea L. Thomaz, Guy Hoffman, and Cynthia Breazeal. Reinforcement learning with human teachers: Understanding how people want to teach robots. In *ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication*, pages 352–357, Sep. 2006.

[71] R. Vallerand, M. Blais, N. Brière, and L. Pelletier. Construction et validation de i'echelle de motivation en educa- tion (eme). In *Canadian Journal of Behavioural Science / Revue canadienne des sciences du comportement*, 1989.

[72] Robert J. Vallerand, Luc G. Pelletier, Marc R. Blais, Nathalie M. Briere, Caroline Senecal, and Evelyne F. Vallieres. The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement*, 52(4):1003–1017, 1992.

[73] Rianne van den Berghe, Josje Verhagen, Ora Oudgenoeg-Paz, Sanne van der Ven, and Paul Leseman. Social robots for language learning: A review. *Review of Educational Research*, 89(2):259–295, 2019.

[74] Basil Wahn, Artur Czeszumski, Melanie Labusch, Alan Kingstone, and Peter König. Dyadic and triadic search: Benefits, costs, and predictors of group performance. *Attention, Perception, & Psychophysics*, 82(5):2415–2433, Jul 2020.

[75] Joshua Wainer, Kerstin Dautenhahn, Ben Robins, and Farshid Amirabdollahian. A pilot study with a novel setup for collaborative play of the humanoid robot kaspar with children with autism. *International Journal of Social Robotics*, 6(1):45–65, Jan 2014.

[76] Erin Walker and Winslow Burleson. User-centered design of a teachable robot. In *Intelligent Tutoring Systems*, pages 243–249, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg.

[77] Erin Walker, Victor Girotto, Younsu Kim, and Kasia Muldner. The effects of physical form and embodied action in a teachable robot for geometry learning. In *2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT)*, pages 381–385, July 2016.

[78] Xing Wang and Alexander Vinel. Reannealing of decaying exploration based on heuristic measure in deep q-network, 2020.

[79] Christopher John Cornish Hellaby Watkins. *Learning from Delayed Rewards*. PhD thesis, King's College, Cambridge, UK, May 1989.

[80] Iain Werry, Kerstin Dautenhahn, Bernard Ogden, and William Harwin. Can social interaction skills be taught by a social agent? the role of a robotic mediator in autism therapy. In Meurig Beynon, Chrystopher L. Nehaniv, and Kerstin Dautenhahn, editors, *Cognitive Technology: Instruments of Mind*, pages 57–74, Berlin, Heidelberg, 2001. Springer Berlin Heidelberg.

[81] Kipling D. Williams. Dyads can be groups (and often are). *Small Group Research*, 41(2):268–274, 2010.

[82] Robert C. Wilson, Andra Geana, John M. White, Elliot A. Ludvig, and Jonathan D. Cohen. Humans use directed and random exploration to solve the explore-exploit dilemma. *Journal of Experimental Psychology: General*, 143(6):2074–2081, 2014.

[83] Tinakon Wongpakaran, Nahathai Wongpakaran, Rojarek Intachote-Sakamoto, and Theerarat Boripuntakul. The group cohesiveness scale (gcs) for psychiatric inpatients. *Perspectives in Psychiatric Care*, 49(1):58–64, 2013.

[84] Chung-Hsien Wu, Jen-Chun Lin, and Wen-Li Wei. Survey on audiovisual emotion recognition: databases, features, and data fusion strategies. *APSIPA Transactions on Signal and Information Processing*, 3:e12, 2014.

[85] Elmira Yadollahi, Wafa Johal, Ana Paiva, and Pierre Dillenbourg. When deictic gestures in a robot can harm child-robot collaboration. In *Proceedings of the 17th ACM Conference on Interaction Design and Children*, IDC '18, pages 195–206, New York, NY, USA, 2018. ACM.

[86] Kaichao You, Mingsheng Long, Jianmin Wang, and Michael I. Jordan. How does learning rate decay help modern neural networks?, 2019.

[87] Cristina Zaga, Manja Lohse, Khiet P. Truong, and Vanessa Evers. The effect of a robot's social character on children's task engagement: Peer versus tutor. In Adriana Tapus, Elisabeth André, Jean-Claude Martin, François Ferland, and Mehdi Ammi, editors, *Social Robotics*, pages 704–713, Cham, 2015. Springer International Publishing.

APPENDICES

Appendix A

Detailed User Study Results

A.1 Demographics and Pre-study Survey Results

The results reported from surveys before the start of the teaching interaction are shown in this section. Figure A.1 shows the distribution of various degrees is similar between the participants of the adaptive and the baseline condition. Figure A.2 compares the participants' prior knowledge and exposure to rocks, robots and conversational agents (CA) and their interest in each. As previously discussed, the only statistically different measure is Figure A.2b. The participants' fluency in English, their familiarity with their co-participants and their desire to teach Gamma is presented in Figure A.3.

A.2 Curiosity Notebook Engagement and Post-study Survey Results

The participants' perception of Gamma surveyed by Godspeed questionnaire is shown in Figure A.4, Figure A.5 and Figure A.6. The rest of the post-study survey measures such as how much they enjoyed working in a team, how much they enjoyed teaching, and their desire for participating in a similar study is demonstrated in Figure A.7 and Figure A.8. The score from both IMI and Motivation Questionnaire in the respective subclasses are shown in Figure A.9 and Figure A.10

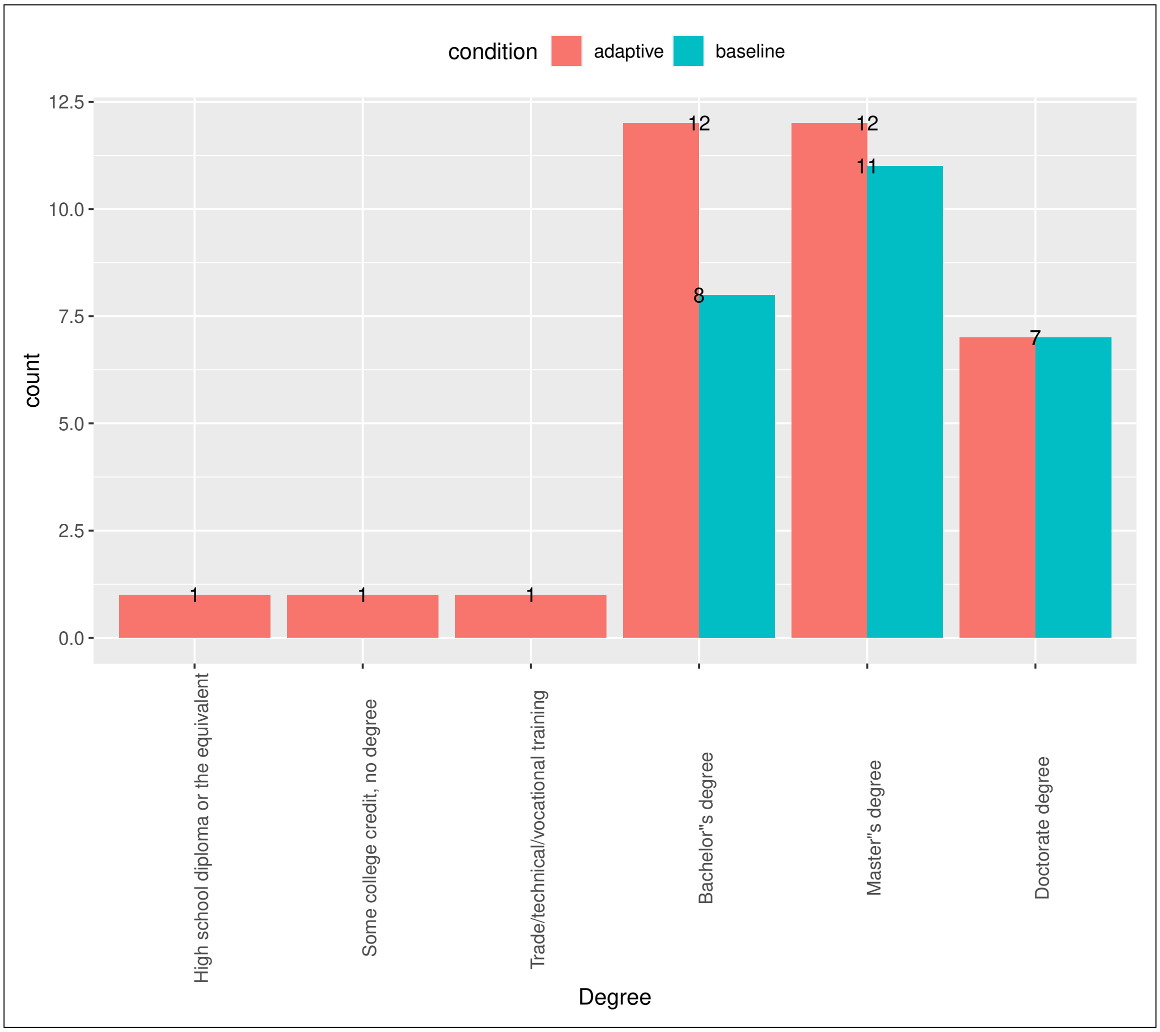
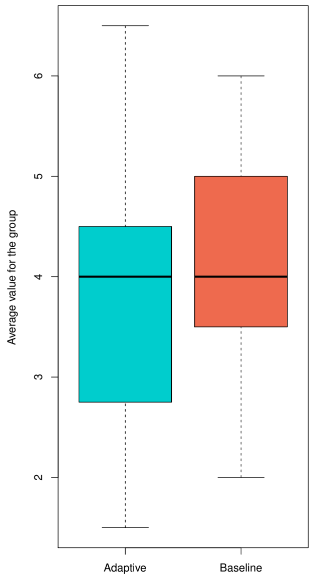
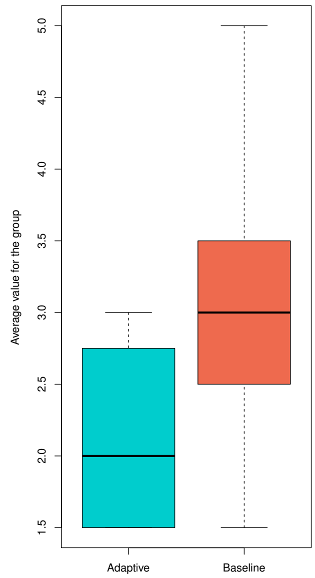


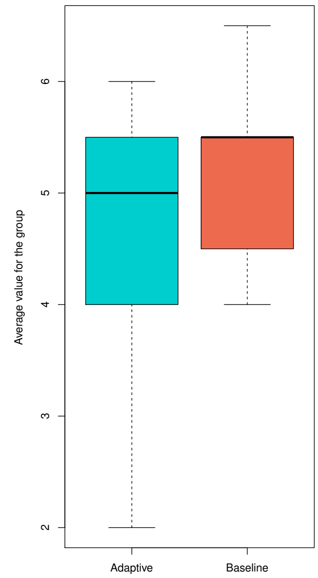
Figure A.1: Highest Degree Completed or Currently Pursuing



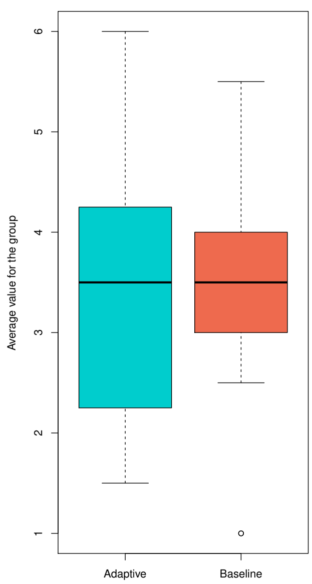
(a) Interest in the topic of Rocks



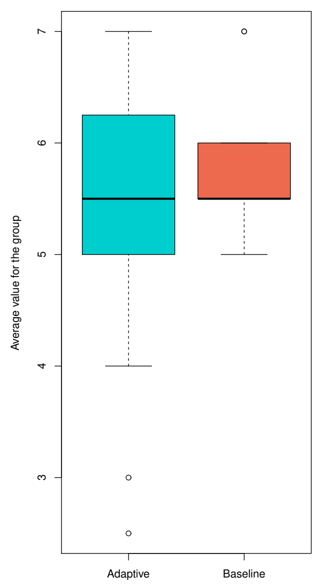
(b) Prior Knowledge on Rocks



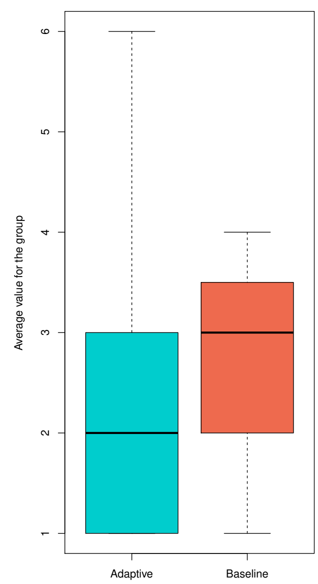
(c) Previous interaction with CAs



(d) Interest in Conversational Agents

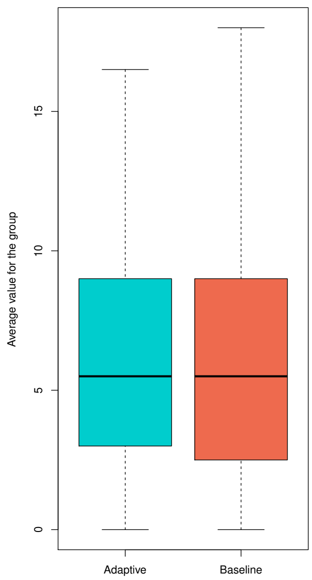


(e) Previous Interactions with Robots

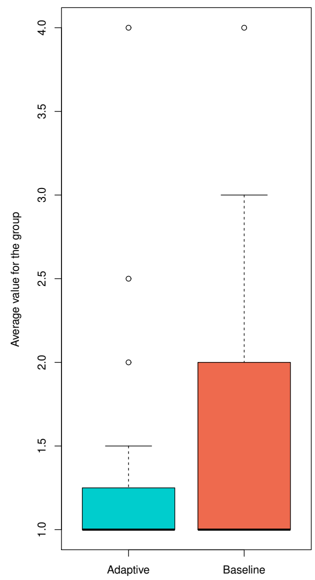


(f) Pre-study Interest in Robots

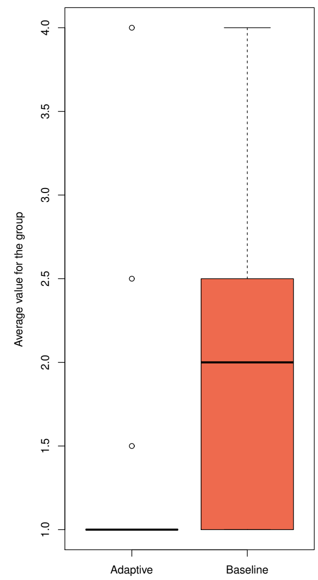
Figure A.2: Interest and prior exposure to the topic, conversational agents and robots



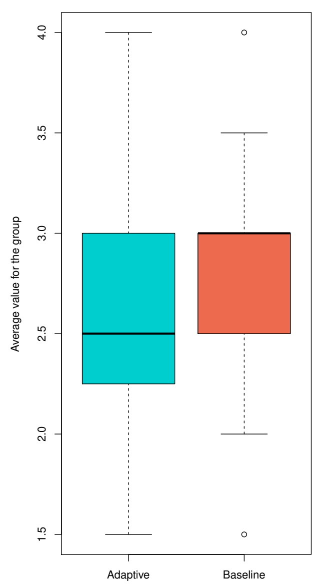
(a) Starting Age of Speaking English as a Second Language



(b) Time Spent with co-participant in classroom and in school

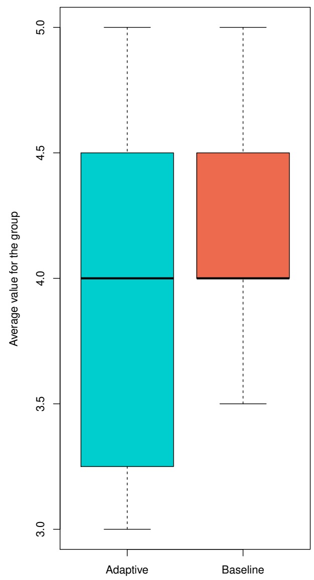


(c) Time Spent with co-participant outside of school

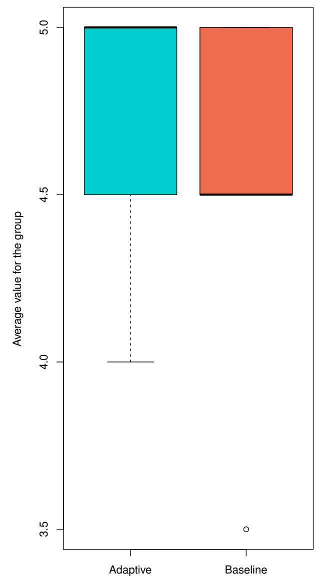


(d) Desire to Teach Gamma

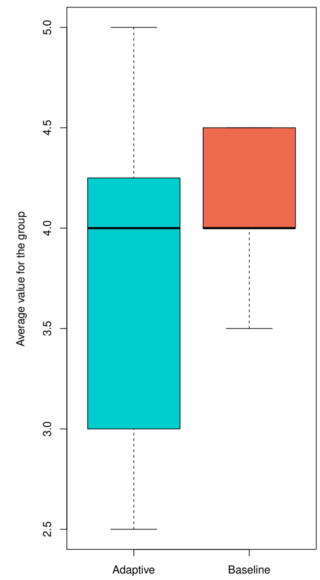
Figure A.3: English Fluency, Familiarity with Co-Participant and Desire to Teach Gamma



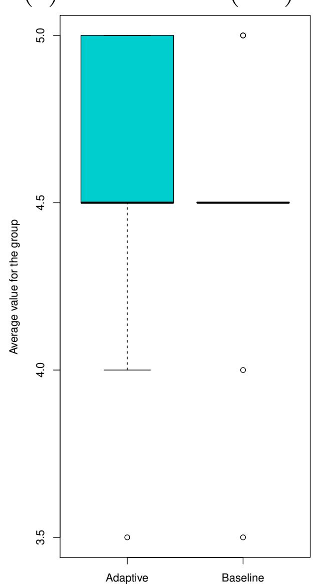
(a) Friendliness (Pre)



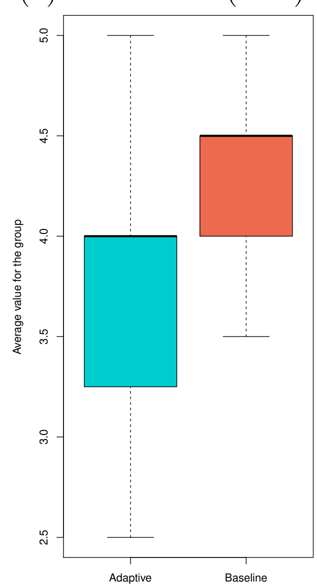
(b) Friendliness (Post)



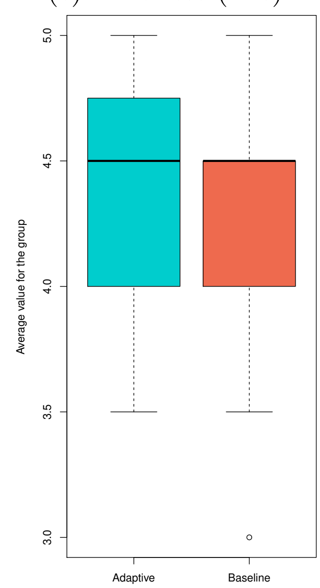
(c) Kindness (Pre)



(d) Kindness (Post)

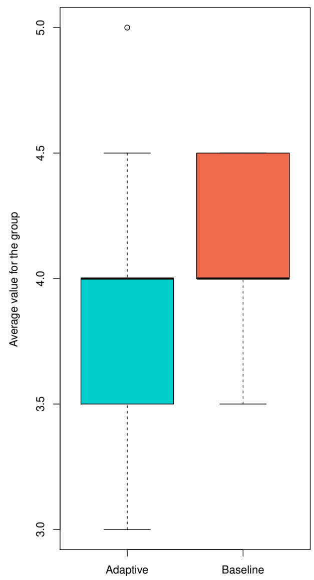


(e) Pleasantness (Pre)

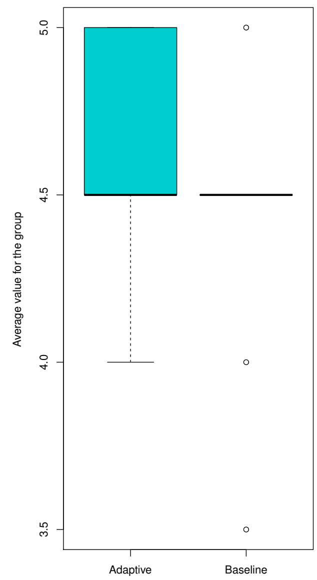


(f) Pleasantness (Post)

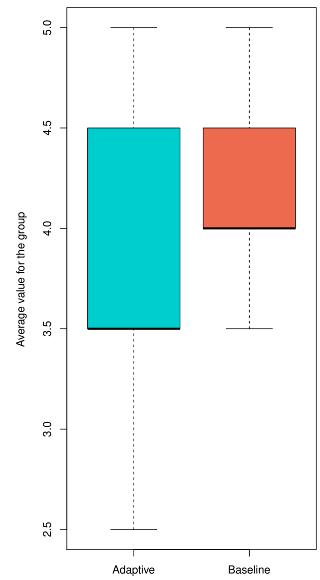
Figure A.4: Pre-study and Post-Study Godspeed Scores: Likeability



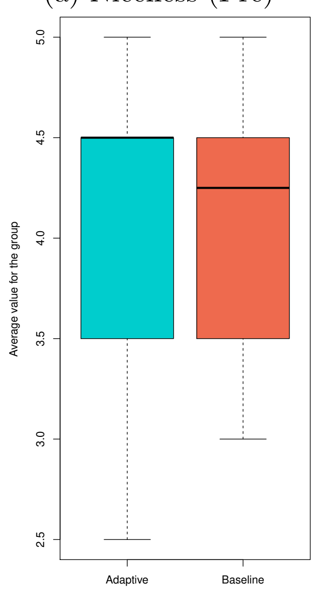
(a) Niceness (Pre)



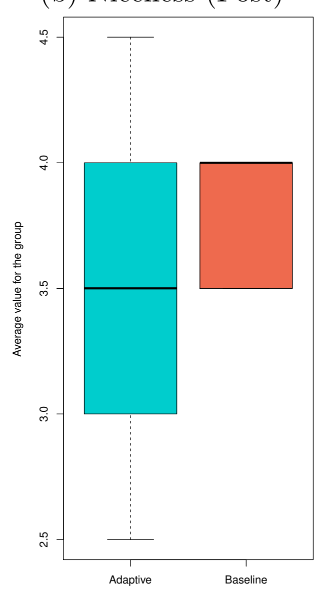
(b) Niceness (Post)



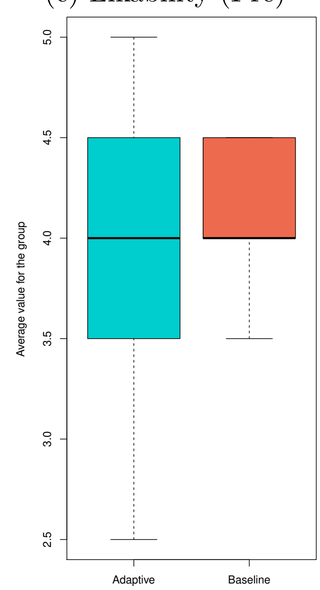
(c) Likability (Pre)



(d) Likability (Post)

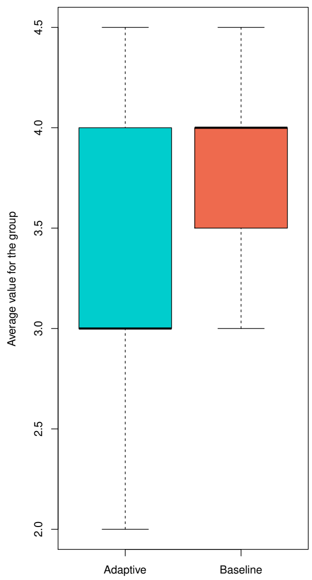


(e) Competence (Pre)

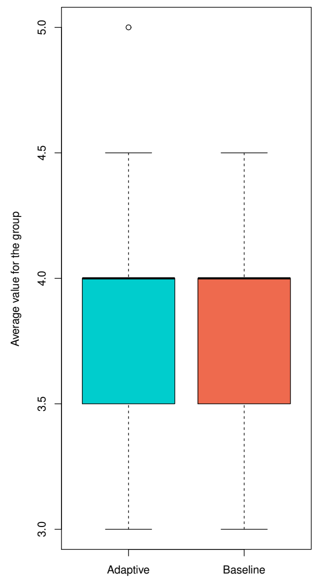


(f) Competence (Post)

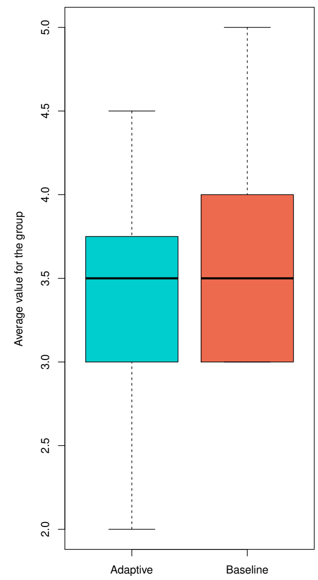
Figure A.5: Pre-study and Post-Study Godspeed Scores: Likeability and Perceived Intelligence



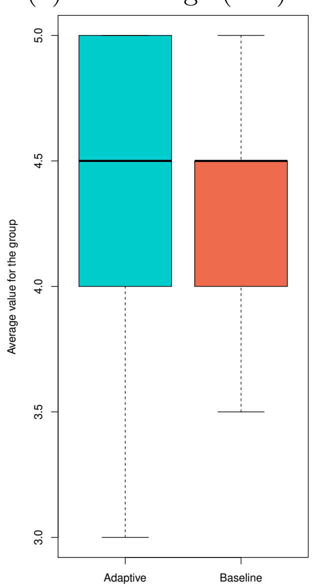
(a) Knowledge (Pre)



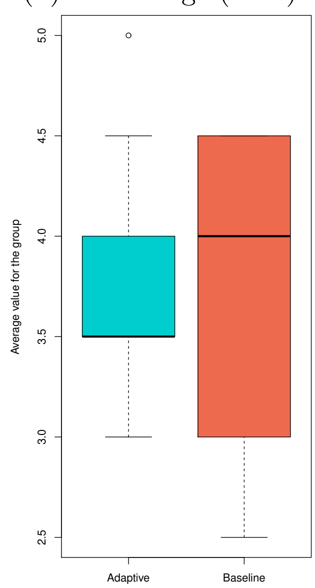
(b) Knowledge (Post)



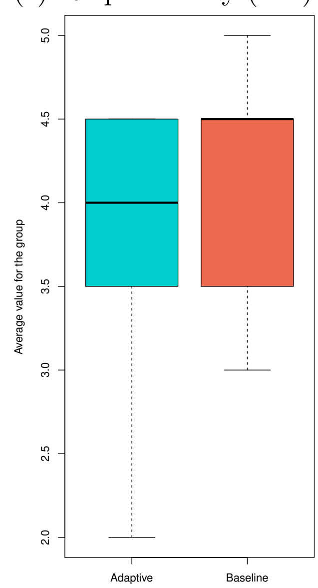
(c) Responsibility (Pre)



(d) Responsible (Post)

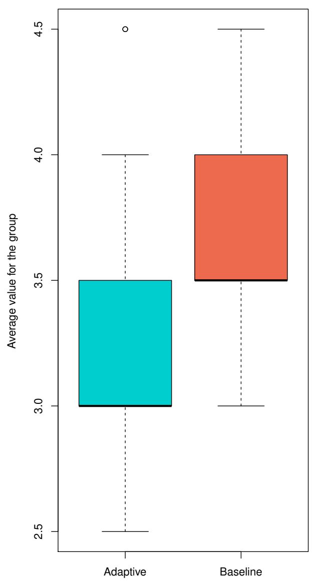


(e) Intelligence (Pre)

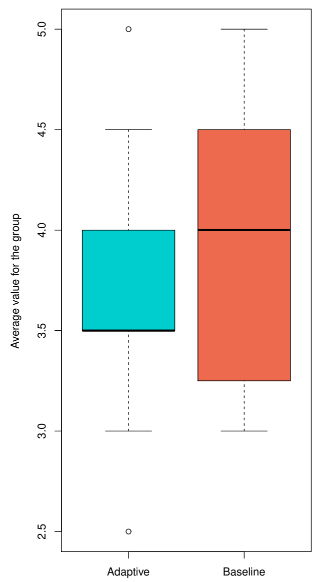


(f) Intelligence (Post)

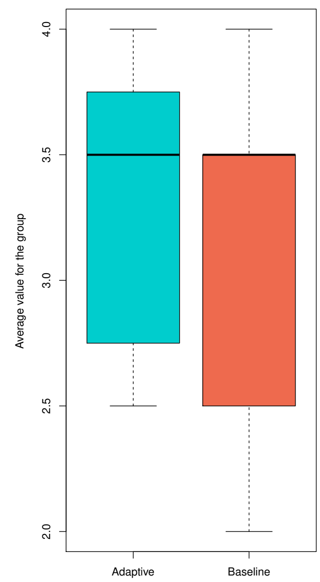
Figure A.6: Pre-study and Post-Study Godspeed Scores: Perceived Intelligence



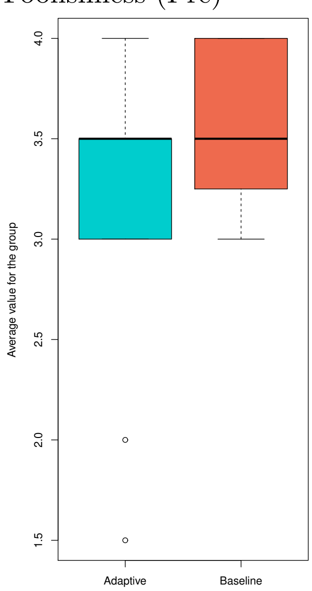
(a) Godspeed Scale Foolishness (Pre)



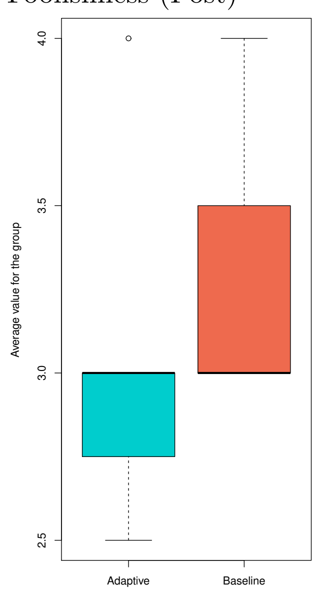
(b) Godspeed Scale Foolishness (Post)



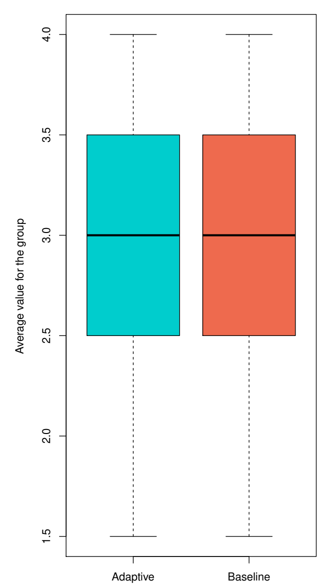
(c) Gamma's Evaluation as a Student



(d) Enjoyment from Working with Co-participant

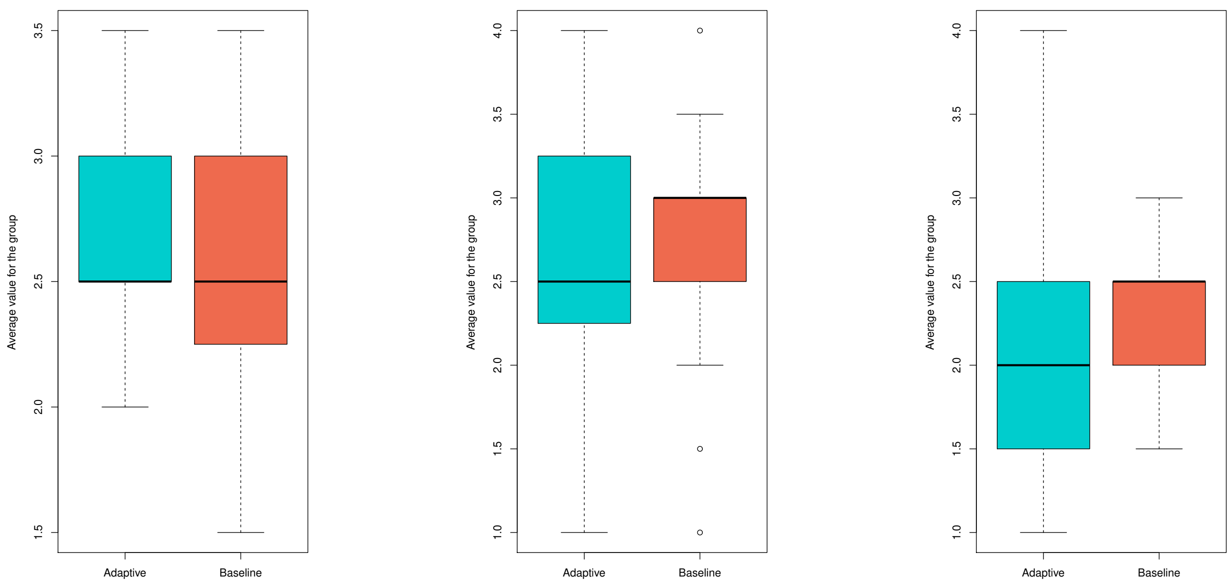


(e) Contribution Percentage to the Teamwork



(f) Enjoyment from Teaching the Robot

Figure A.7: Perception, Enjoyment and Contribution

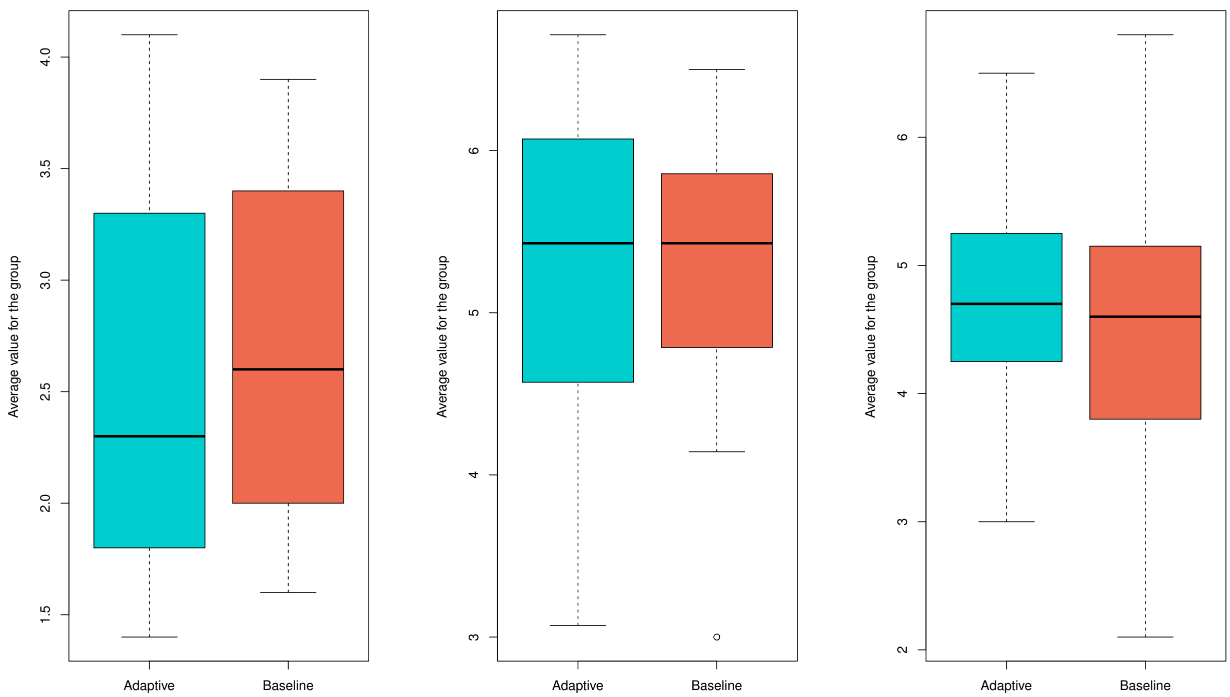


(a) Self-evaluation as a Teacher

(b) Interest in Teaching Gamma Again

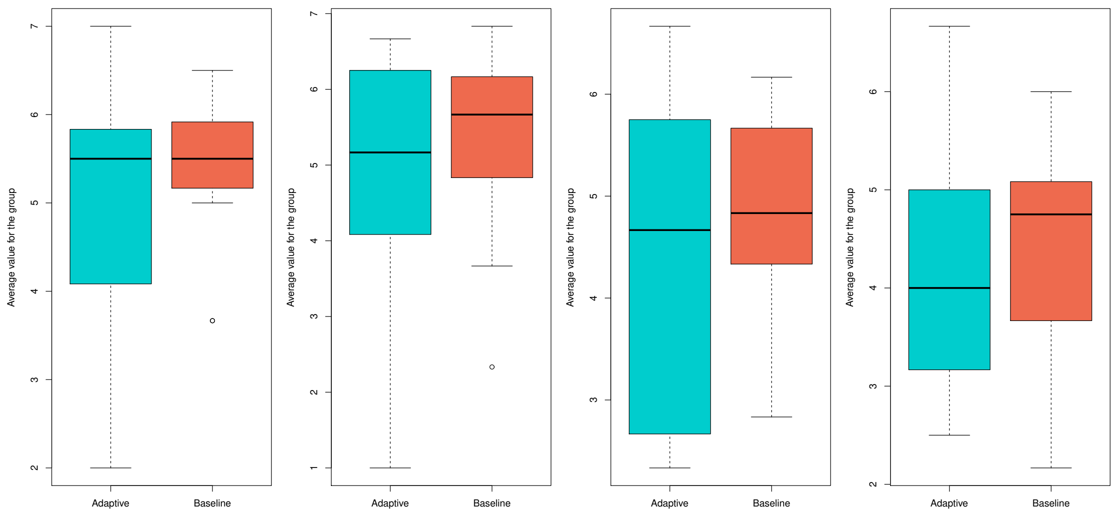
(c) Interest in Learning More about Rocks

Figure A.8: Interest in Repeated Participation

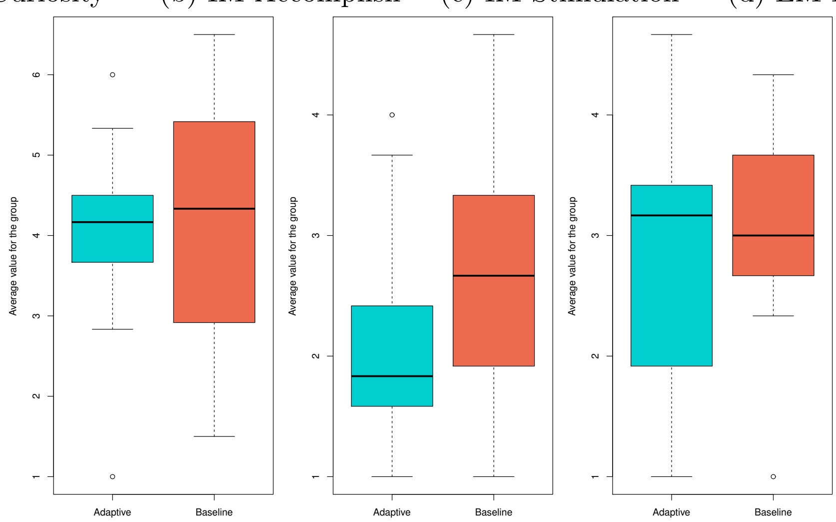


(a) Pressure/Tension (b) Interest/Enjoyment (c) Effort/Importance

Figure A.9: Intrinsic Motivation Inventory Results shown in 3 Subscales on 7 Point Scale Likert



(a) IM-Curiosity (b) IM-Accomplish (c) IM-Stimulation (d) EM-Identified



(e) EM-Introjected (f) EM-Regulation (g) Amotivation

Figure A.10: Intrinsic Motivation (IM), Extrinsic Motivation (EM) and Amotivation Questionnaire Result on 7 Point Scale Likert