Abstract

Building Effective Robot Tutoring Interactions for Children

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Socially assistive robots have the potential to assist people in a variety of social and cognitive tasks, often taking the role of a coach or tutor to support users over time. For educational applications, robot tutors have been shown to be successful in diverse domains, including providing one-on-one math tutoring [115], facilitating social skills training for children with autism [76], and teaching sign language to deaf infants [203]. Early work in the field of Human-Robot Interaction (HRI) has shown the advantages of physically-present robot tutors in fostering increased attention, engagement, and compliance, which are critical components of successful tutoring interactions [18, 143, 168]. In order for social robot tutors to be effective tutors for children in real-world environments and have the potential to impact education, it is critical for us to understand what behaviors and mechanisms social robot tutors can employ to support self-efficacy in students and enhance their learning.

The work in this dissertation seeks to identify personalization strategies and techniques for building effective social robot tutors that enhance learning outcomes for children. It investigates practical guidelines for how robot tutors can sustain engagement, support metacognitive strategy use, shape productive help-seeking behavior, and provide personalized help actions to children in a tutoring setting. In order to understand these important aspects of robot tutoring interactions, we build several autonomous robot tutoring systems and systematically study whether novel personalization strategies that can be employed by a robot tutor can positively impact learning outcomes for students.

We identify several personalization mechanisms and support strategies that have never been previously explored within the context of robot-child tutoring and demonstrate their potential to make tutoring interactions more effective. We first identify non-task breaks provided to students after performance drops as a practical mechanism for maintaining engagement during a cognitively taxing interaction. Following this, we consider robots that

support metacognitive strategy use and highlight the benefits of both a physically-present robot tutor and a particular metacognitive strategy called “thinking aloud”. Moving toward longer-term interactions that last multiple sessions, we identify help-seeking behavior as another salient aspect of tutoring that contributes to learning gains for students, showing that robot tutors that employ strategies to shape unproductive behavior enhance learning gains. We also demonstrate the value of a personalized approach to providing assistance to children in a longer-term tutoring setting, showing that a robot tutor that selects help actions based on a real-time estimate of a student’s knowledge and engagement leads to more effective learning.

We present two more general frameworks for designing robot intervention behaviors during tutoring settings. The first framework is a more intuitive pipeline that leverages the relationship between unobservable user states and observable behavior within a tutoring system and identifies unproductive behaviors from students that would benefit from robot intervention. We demonstrate the usefulness of this framework by correlating measures of student motivation to unproductive hint use and designing robot intervention behaviors to specifically counter these unproductive behaviors. Our second model is a more general, computational approach to autonomously planning help actions to give to students in a one-on-one tutoring interaction. It relies on a student model that incorporates information about both the knowledge and engagement levels of a student and continuously updates its belief of these states through observations of a student’s progress. In our instantiation of the model, we derived parameters from our own prior tutoring data and included help actions based on design recommendations from our prior studies (such as breaks and thinking aloud). This model can be used more flexibly in a variety of different tutoring settings and provides a unified method to both model the student’s state and select supportive actions to individual students of varying abilities over time.

Building Effective Robot Tutoring Interactions for Children

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Chapter 1

Introduction

The field of Human-Robot Interaction (HRI) has made great strides towards understanding what makes effective interactions between robots and people. In particular, socially assistive robotics (SAR) explores how robots can be used to help and support people cognitively and emotionally through the use of social behavior. In recent years, social robots have become increasingly capable of establishing and maintaining supportive relationships with humans in a variety of application domains, such as educational tutoring [116], collaborative manufacturing [97], and household services [39].

Of these application domains, the field of education has significant potential to benefit from the use of social robots. There has been a large body of research demonstrating that students that receive one-on-one tutoring perform, on average, significantly better than students learning via conventional classroom instruction when tested on the same material [36, 224]. Because schools and educational systems lack the resources to provide a one-on-one tutor to each individual student, other methods of instruction that will emulate the benefits of one-on-one human tutoring must be explored. Among the large variety of learning technologies available, social robots have shown great promise as tutoring agents. Research investigating the use of robotic tutoring agents indicates that the physical presence of a robot tutor can increase cognitive learning gains [143]. In addition, various human-robot interaction studies have shown that physical robot tutors may increase engagement [168] and compliance [18] in students, which are critical aspects of a learning interaction. These early research efforts motivate the need to more deeply investigate robotic tutoring systems as an effective method of instruction.

In the last few years, HRI research has demonstrated that social robots can be leveraged to improve various educational interactions by impacting cognitive and affective outcomes of students [34]. However, understanding how to build truly effective robot tutors is still an open problem that involves many technical challenges. Learning is a complex cognitive process that involves many crucial factors that are difficult to sense and understand, such as motivation level and affective states, as well as other highly individual factors such as learning styles and preferences. Due to the complexity of the one-on-one tutoring space, using social robots effectively in educational settings is far from being a solved problem. First, robots must be able to appropriately sense the learning environment, which is particularly challenging in a tutoring setting. Complex user states are often unobservable and are difficult to sense and interpret by machines. Being able to estimate nuanced social behaviors such as engagement, motivation, and learning-centric affect is an active area of research. Provided that the robot tutor can perceive or at least estimate its surroundings, robots must be able to perform proper action selection that advances the goals of the student within the learning interaction. What types of social behavior the robot should employ to support the student is still an open research question. In addition, there are often multiple strategies that could be employed from the educational psychology literature as well as techniques studied in human-human tutoring, and understanding how these established practices apply to robot tutors still requires much research and investigation. Finally, much of the research on robots in education has focused on personalizing tutoring interactions to the individual user. Learning is a very individualized process and robots must personalize their actions and behaviors to each student in order to maximize their effectiveness. However, there are many salient aspects to a tutoring interaction, making the design of personalized behavior for the robot a vast and rich area of research to explore.

This dissertation focuses on the action selection problem for robots in education and investigates a variety of novel behavior mechanisms that social robots can employ during tutoring to improve learning outcomes. To do so, we identify several salient aspects of learning and describe three controlled user studies demonstrating how robots can personalize their behavior based on these factors thereby improving the effectiveness of tutoring interactions. We build on existing HRI research showing that physically-present agents provide educational advantages for students, and focus our research on understanding what social and behavioral mechanisms can further improve learning for students within a robot tutoring interaction. We describe an intuitive architecture that can be used to design simple robot intervention behaviors that account for user attributes and have the potential to impact learning. After investigating several unexplored supportive behaviors a robot can provide in a tutoring scenario, including providing breaks during an interaction, supporting the use of a metacognitive strategy, and shaping student help-seeking behavior, we develop a computational model for action selection that a robot can employ in a tutoring scenario to autonomously provide help to a student. We validate the model's use in practice by conducting a fourth user study that compares students receiving help according to the model's action selection and students receiving help actions based on a fixed set of rules.

Though a significant amount of research and other studies have focused on the efficacy of social robots in educational settings, much of that work has been conducted with adults, in laboratory settings, using teleoperation, or over single short-term tutoring sessions. The user studies described in this work strive specifically to validate autonomous robot tutoring systems used with children in school settings over both short-term and longer-term durations. We investigate supportive behaviors that robot tutors can employ within learning scenarios that have not been previously considered within HRI research on robots for education. We also build on findings from our user studies to develop a more general computational action selection model for a robot tutor that provides help actions to students during tutoring and we demonstrate the effectiveness of our computational model with another long-term controlled user study with children in schools. The methods in this dissertation leverage techniques from computer science and educational psychology to build robust intelligent and interactive robot tutoring systems that improve student learning outcomes, making this work interdisciplinary in nature.

This dissertation begins by providing a comprehensive review of the work that has been conducted on robots for education (Chapter 2). This background chapter details the body of work that has demonstrated why we believe social robots make effective tutoring agents. It covers work in a related field, intelligent tutoring systems (ITS), as well and differentiates why physically-embodied tutoring agents provide advantages in educational scenarios when compared with other available technologies to support learning. It further outlines the open challenges within robot tutoring and motivates why we conduct empirical studies of robot tutors personalizing their behavior to improve learning for children.

The following chapters (Chapters 3-5) describe carefully designed user studies that expand our understanding of specific robot behavioral mechanisms that enhance learning during tutoring. Tackling the broader problem of designing effective behaviors for robot tutoring interactions, the work discussed in these chapters each follow a process of identifying salient aspects of tutoring interactions and building an autonomous tutoring system that employs personalized robot behaviors that incorporate the specific aspect of the interaction being investigated. This is followed by evaluating the effectiveness of the personalized behavior strategies through a controlled user study with robots tutoring children in the context of a math-based task.

Chapter 3 starts out by examining a fundamental aspect of robot-child tutoring, namely the role of attention and engagement in a learning interaction. Attention is a critical factor in the learning process, yet young children typically have shorter attention spans especially during lengthy tutoring interactions. We built personalized robot behavior strategies to tackle this problem and investigated whether providing breaks to children at the right time during a cognitively taxing math tutoring interaction is effective in improving measures of performance during the tutoring interaction. This study demonstrates that providing these much-needed breaks to students at a time that is personalized to them can benefit student learning and performance both during and after the interaction. This provides a basis for the rest of the dissertation and highlights the ongoing theme of this work: that responsive, personalized behavior mechanisms are crucial in enhancing the success and learning of students in robot-child tutoring interactions.

Chapter 4 then attempts to build on the idea that the embodied social presence of robots can be leveraged to keep students engaged during learning as well as to enhance their ability to utilize problem-solving strategies they may typically struggle with. Because social robots can typically maintain engagement during learning more effectively than other learning technologies, we wanted to leverage this idea to further understand how a social robot can bolster metacognitive strategy use for children during tutoring. Metacognitive strategies are extremely important for students to become successful learners; however, many students struggle with monitoring their own learning and employing high-level strategies for becoming better problem solvers. The experiment described in this chapter looks at how social robot tutors can interactively support students' use of a particular megacognitive strategy, called thinking aloud, during a tutoring interaction in which students complete complex word problems. This study provides additional evidence that the social presence of the robot enhances learning by showing increased engagement and compliance when the think-aloud support is delivered by a robot and further reveals the benefits of both the robot tutor and the think-aloud strategy itself on learning gains.

After investigating how robots can support children using one particular metacognitive strategy, thinking aloud, we sought to better understand another metacognitive behavior within learning, namely help-seeking behavior. Chapter 5 describes an architecture for designing simple robot intervention behaviors and is empirically validated through a long-term user study in which a robot tutor counters unproductive help-seeking behavior. This process demonstrates a feasible way to incorporate important user characteristics in the design of robot intervention behaviors to improve the potential success of the robot tutoring interaction. Furthermore, the user study described in this chapter reveals that social robot tutors that employ simple, personalized behavior strategies aimed at countering ineffective help-seeking behavior leads to improved behavior and learning over time.

After conducting these studies and developing a better understanding of salient behavioral mechanisms that robots can employ to improve learning, we build a computational model that allows a robot tutor to autonomously select help actions during a tutoring interaction in a way that is personalized to each child. Chapter 6 describes this model and its computational techniques, and includes the data-driven design decisions that went into its creation. This model incorporates results and lessons learned from the three user studies described in the preceeding chapters to create a more general computational architecture for a robot to employ to provide personalized help to students during a one-on-one tutoring interaction. Our computational model is then validated in another long-term user study in which students receive supportive help during tutoring as dictated by our model over multiple tutoring sessions. This study ties together all the work we have conducted thus far on effective robot-child tutoring interactions; it incorporates both breaks and thinking aloud, as well as autonomous help action selection based on personalized modeling of student knowledge and engagement in real-time.

In Chapter 7, we presesnt a broader discussion of the research conducted in this dissertation. We highlight the contributions of this work along with its broader implications. We also discuss limitations and outline future directions that should be explored. In Chapter 8, we provide a summary of the work conducted in this dissertation.

This dissertation makes the following contributions to advance the understanding of building effective robot tutoring interactions for children: (1) the identification of novel behavioral mechanisms for robots to employ within a one-on-one tutoring interaction validated to provide evidence-based design recommendations for enhancing learning and performance during tutoring; (2) an architecture for designing robot intervention behaviors during tutoring that takes into account unobservable student characteristics, such as motivation; (3) a robust computational model for providing personalized help actions to students, which was developed based on data and design choices from our own user studies involving robot tutors for children.

Chapter 2

State of the Art: Robots for Education*

This chapter provides a comprehensive review of technology-based tutoring systems, with an emphasis on the use of robots in education. We start by discussing why one-on-one tutoring is important, what we have learned from successful human tutors, and how the field of intelligent tutoring systems (ITS) has explored many challenges in building effective tutoring agents. We then look at why physically embodied robot tutors are currently being explored as effective learning technologies, specifically for children. We describe several critical aspects of robot tutoring that are currently being investigated by researchers in this field, including current practices such as platforms used and common measures used in tutoring interactions. We detail the progress that has been made thus far and specifically highlight efforts made to build personalization into tutoring systems, demonstrating the efficacy of robot tutoring systems in a variety of application domains. We also mention current challenges to building effective robot tutoring systems, indicating the vast amount of research still required in this domain.

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2.1 The Benefits of Human Tutoring

There has been a large body of research demonstrating that students that receive one-on-one tutoring perform, on average, one to two standard deviations better than students learning via conventional classroom instruction when tested on the same material [36, 224]. Ideally, each individual student would have access to one-on-one tutoring in order to strengthen learning, especially for those who may have fallen behind. However, because many schools lack the resources to provide this support to each student, there is an open search to uncover other processes or tools that may emulate the benefits of one-on-one human tutoring. With technology and computers becoming more prevalent in the educational domain, computer-based tutoring systems as well as robot tutoring systems are being investigated as effective platforms to aid student learning. In order to design effective tutoring agents, research in education has studied what strategies and techniques successful human tutors employ to help students.

A comprehensive review by Lepper and Woolverton cited three factors as advantages of one-on-one tutoring compared to larger group or classroom instruction: individualization, immediacy, and interactivity [141]. One-on-one tutoring involves an individualized interaction, allowing the tutor to closely attend to the student, and provide personalized responses and feedback, which is not possible in a classroom setting (with a teacher attending to 30 students, for example). Tutoring also affords greater immediacy—the timing of feedback and corrections the tutor can provide to the student—which can be critical for learning. Tutors can provide just-in-time feedback, correcting misconceptions as they occur. This is much more immediate than traditional classroom feedback, which often provides corrected homework after several hours or days. The level of interactivity is also typically much higher in one-on-one tutoring as compared to classroom instruction, as students typically talk as they reason and tutors can intervene at any time with a variety of assistance (questions, feedback, hints, encouragement, etc.) based on their estimation of a student's current cognitive and affective capabilities.

Lepper and Woolverton's review also closely studied the techniques that expert human tutors used and found that human tutors spend a lot of time providing motivational and affective support in addition to providing help and assistance on the domain-related content. In addition, human tutors are nuanced and subtle in their support, asking the student questions and providing the smallest level of assistance required to allow the student to learn independently [141, 157]. Successful tutors also present problems and examples based on their assessment of student skills, correct errors as they occur, and encourage students to persist through challenges [141]. These strategies contribute to the effectiveness of one-on-one tutoring interactions for students.

The study of what makes human tutors so successful has inspired research into how computer-based tutoring systems can emulate these benefits [157]. Below we review common techniques used in intelligent tutoring systems that attempt to replicate the success of human tutors using screen-based tutoring technologies. We then describe the newer field of robots for education, which also draws from insights on human tutoring and the findings of successful intelligent tutoring systems.

2.2 Intelligent Tutoring Systems

The field of Intelligent Tutoring Systems (ITS) has been working towards building effective screen-based tutoring systems for several decades. ITSs are typically made up of four components: the student model which represents a student's current state of knowledge, the tutoring model which provides pedagogical tactics such as providing feedback and hints, the domain model which contains expert knowledge on concepts and rules of the learning domain, and the user interface which dictates how the student interacts with the system to communicate and receive knowledge [56]. Most work in this domain has sought to understand effective tutorial strategies that can improve student use of the system and impact learning. In this process, researchers in ITS have investigated many modeling approaches to track student progress and have explored what types of help and assistance can be provided in a tutoring system to aid students in learning. For a recent review, see [128].

2.2.1 Types of Tutoring Systems

There have been several major approaches to providing tutoring and support to students in intelligent tutoring systems. Some tutoring systems provide focus on ordering content according to student ability, which are typically called curriculum sequencing tutors [63,84]. These systems typically assess performance on certain concepts and present students with practice opportunities or instructional content based on areas the student might be weak in. Content sequencing systems make more general assessments of a student's knowledge on concepts or material and can provide recommendations at various levels of granularity, such as at the level of individual problems or at the level of book chapters or courses [63]. One of the most widely used curriculum sequencing tutor, now a commercialized product called ALEKS, provides an online environment for students to practice math concepts and gives practice exercises to students based on what concepts should provide an appropriate amount of challenge for them [40].

Another family of ITSs are called model-tracing tutors, a term originally coined in 1985 [12]. As opposed to curriculum sequencing, which changes the behavior of the tutoring system at the granularity of what exercise to provide, the model-tracing approach focuses on fine-grained feedback on intermediary steps rather than just the entire problem [83,226]. The approach is modeled after human tutors that are able to provide feedback at any point during an interaction based on real-time errors or misconceptions that the tutor can detect from interacting with the student. Trying to emulate this practice, the idea is that just-in-time feedback to students would help them identify where their errors or misunderstandings lie and may enable them to correct their errors more easily than with more general feedback (such as finding out whether the entire problem is correct or incorrect). Some systems have successfully implemented this approach, many of which deal with subjects such as math or physics, where tutoring content can be distilled down to individual problem steps that have answers that can be easily assessed as correct or incorrect [186,226]. A popular family of intelligent tutoring systems called Cognitive Tutor was used widely in schools to help students practice math skills including algebra and geometry, and were shown effective in increasing learning [13,123,124].

Speech is an important channel of information in a tutoring interaction. Unfortunately, even with current advances in speech-to-text technology, it is still difficult to parse, understand, and respond in real-time, especially with children [80, 118]. Some tutoring systems have bypassed the problem of relying on speech, and instead have students type dialogue as input into the system, allowing them to use natural language to communicate [73, 90, 147]. By having the typed text from the student, the tutoring system can attempt to understand the student's questions or responses and generate dialogue to respond, often using a virtual avatar to deliver this generated speech. One system that does this successfully is called AutoTutor and has been used to tutor students in the domain of physics [90]. This system uses a pattern-matching technique that evaluates similarity between two pieces of text to parse typed dialogue from the student and evaluate student explanations relative to correct concepts and answers [130]. However, this approach only works well for adults who can adequately explain themselves and domains in which correct responses can be assessed by the presence of words in text (such as describing a conceptual physics problem instead of solving a math problem).

2.2.2 Student Modeling

One of the most important components of an intelligent tutoring system is the student model. Many of the systems described above make their tutorial decisions based on their estimate of what the student "knows" as assessed by the student model component in the system. The most widely used tactic for modeling student knowledge is a method called Bayesian Knowledge Tracing (BKT) [55]. This approach is used to model student knowledge during the process of skill acquisition and probabilistically models each individual knowledge component of a skill as either learned or unlearned [55]. For each skill, there is a Hidden Markov Model (HMM) with two hidden states: learned and unlearned, and there are two observations in the BKT algorithm that are binary, where a student either enters a valid answer or an invalid answer for a given problem step [20]. There are four model parameters typically used in a BKT, including the initial probability that the student knows the skill ($p(L_0)$), the probability of a skill being learned on a given practice opportunity ($p(T)$), the probability of a mistake using a known skill ($p(S)$), and the probability of guessing correctly using an unknown skill ($p(G)$). Tutoring systems that employ BKT have successfully been used to tutor concepts such as math and programming skills [55, 122]. Though this is an effective technique for modeling a student's knowledge state, the computational focus is on accurately estimating student knowledge of individual sub-skills, rather than determining optimal action selection in a tutoring scenario. Most tutoring systems that use this approach use the estimated knowledge level to inform content selection depending on whether a fixed mastery threshold is reached [131, 234].

There have been other computational approaches to modeling various aspects of the tutoring process, including fuzzy logic, dynamic bayesian networks, and reinforcement learning [46, 51, 213]. Some work leverages prior student data to train various machine learning classifiers (such as decision trees and Bayesian classifiers) to inform their predictions of whether a student will answer the next question correctly, and uses that information to inform intervention strategies [32]. Other work has investigated using dynamic bayesian networks to handle the inherent uncertainty in understanding a student's knowledge state during tutoring interactions [51]. Chi et al. applied reinforcement learning to a dataset of pre-existing human tutoring interaction data and found that the learned tutorial tactics made a difference in student learning [46]. Recent work has explored employing Partially Observable Markov Decision Processes (POMDPs) to plan teaching actions in a tutoring setting [79, 176]. POMDPs can model a learning scenario because the student's state is only partially observable, however these methods often do not scale well to real-time systems for application domains that are complex. It is still a focus of ongoing research to build systems that can apply existing algorithms and techniques that handle planning under uncertainty to real-world application domains, such as action selection for robot tutors in one-on-one interactions.

Though many of these machine learning methods, including BKT, have been applied to student modeling, there are several limitations making them difficult to use in real-time applications. One limiting factor for educational applications is that they often require large amounts of training data, which small scale user studies do not typically generate. In addition, methods such as reinforcement learning that require positive or negative feedback can be challenging to apply to a real-world tutoring setting. This is because learning is a complex cognitive process making it hard to define measures of objective success and failure in a tutoring interaction. The exploration phase of employing reinforcement learning algorithms also make it challenging to try out different tutorial tactics on a given student as this can require a large amount of trials, which may be unrealistic to do in tutoring settings with children.

2.2.3 Feedback and Assistance in ITS

The field of ITS has also focused on understanding and developing several forms of help that can be used to assist learners. Below we list some of the most common types of help used in tutoring systems.

- *Hints*, or help messages, are one of the most common forms of help. One of the most widely used and tested tutoring systems, Cognitive Tutor, has used multiple levels of help messages, which are available to the student on-demand in the following order: (1) a message outlining the problem-solving goal, (2) a message drawing attention to specific features of the problem, and (3) a "bottom-out hint" specifying the actions needing to be taken to solve the problem [11]. Other tutoring systems have similar structuring of hints, often with even more levels of hints available [5]. Hints are typically delivered in order, where subsequent hints contain more specific information to solving the problem at hand. Though some systems decide when to provide hints to students, many systems provide hints on-demand, or whenever the student requests it.

- *Worked examples* refer to problems that show all the necessary steps to solve them successfully. Worked examples have been shown to be an effective form of help in tutoring systems [15, 155]. There has also been evidence that novice students prefer to learn from an example rather than instructions describing how to complete the problem [134]. However, generalizing a concept or skill from an example and applying it with independence is not easy for all learners.

- *Self-explanations* are defined as the generation of explanations to oneself and have been shown to improve understanding [47]. Requests for self-explanations can also encourage the student to describe their thought process out loud, which allows them to potentially catch errors in their reasoning and fosters better understanding [47,174]. This process can also be referred to as thinking aloud which has been investigated as a metacognitive strategy and has led to improved performance [6,81]. However, students are not always successful at generating these types of explanations spontaneously and it can also be an additional cognitive burden that leads to lower performance [222].

- *Step-based tutoring* refers to tracking progress of individual steps in a problem and providing feedback on these intermediary steps rather than all at once after the student provides an answer [124,224,226]. These advantages have led to the creation of several tutoring systems that provide more fine-grained feedback in the form of an interactive tutorial for a given problem, leveraging the idea that more interactivity and feedback on each individual step may lead to stronger understanding of where a misconception occurs [224].

Prior work has often focused on directly comparing different types of help [156]. For example, Ringenberg and VanLehn specifically compared hints and worked-out examples in tutoring college-level physics, finding that worked-out examples were more efficient than procedure-based hints in the number of problems it took students to obtain basic mastery [185]. While this work directly contrasted the two types of help, it does not address how multiple types of help can be used in combination to lead to the best learning environment for a student. Renkl developed a set of principles called SEASITE (Self-Explanation Activity Supplemented by Instructional Explanations) to outline how help can be deployed to facilitate learning for students, leveraging the power of self-explanations with the knowledge a tutoring system can provide [182]. The principles suggest providing help by first eliciting as much self-explanation (requesting the student to think aloud) as possible from the student and then providing instructional explanations, progressing from minimalistic to extensive.

2.2.4 Evaluation Metrics

Evaluating the effectiveness of a tutoring agent is not trivial, as each agent interacts with many different learners, and each individual interaction can be complex. We list a few evaluation metrics commonly used for existing tutoring systems. These metrics are used to evaluate both non-embodied tutoring systems as well as robot tutoring systems. We first provide a discussion of how learning is commonly assessed in tutoring systems and some of the advantanges and drawbacks associated with different approaches.

- *Learning Gains*: This metric refers to how much a student learns during the course of an interaction. Assessment in education is a complex problem due to the highly individualized nature of learning. For tutoring interventions in particular, it becomes challenging to measure learning gains in an identical way for all students. Nonetheless, in an effort to standardize how progress is measured across a wide range of students, this is typically measured by the difference in pretest score ($score_{\text{pre}}$) and posttest score ($score_{\text{post}}$) to see how much improvement is made [90]. Pretests and posttests are often scored by awarding points out of the total number of possible points, resulting in scores between 0 and 1. There is some debate as to whether pretest scores necessarily impact learning gains, or the ability to demonstrate improvements between the pretest and posttest. However, most in the ITS community find it important to account for the student's pretest score in some way, by using a difference score to capture gains or by using a covariate approach. Furthermore, in running controlled user studies to evaluate the effectiveness of an intelligent tutoring system, it is often difficult to guarantee that each experimental group will be homogeneous in terms of factors that may impact learning, even when randomly distributing participants into groups. Due to this, it is important to utilize a metric that accounts for incoming knowledge level. In order to control for various incoming knowledge levels on pretest measures and ensure that each student has the same potential opportunity to demonstrate improvement, studies evaluating the effectiveness of a tutoring system can look at *normalized learning gains*, or nlg for each student i:

$$nlg(i) = \frac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{1 - score_{\text{pre}}(i)} \tag{2.1}$$

In order to evaluate the impact of a certain tutoring system, researchers often compare students who use the tutoring system to some type of control condition, and compare average learning gains or nlg between the groups.

There are certain advantages and drawbacks to each of these approaches. Using a pretest before the tutoring intervention and a posttest afterward relies on students to be able to demonstrate their knowledge and improvement in knowledge without errors that are unrelated to the task at hand (for example, if a student is having a bad day during the posttest, that might not accurately represent their progress). However, the pretest/posttest approach is one of the only standard ways to measure learning gains consistently across students who interacted with the system. Furthermore, using a raw difference in scores to calculate gain does not provide all students with the same potential scoring opportunity. In this case, a student who scores very low on the pretest has a larger potential gain to achieve than a student who scores higher on the pretest. In an example test with five items, it may be considered more difficult for a student to improve from .80 to 1.00 than from .00 to .20.

To account for this, the metric of normalized learning gain can be used. Normalized learning gain was first introduced in the physics education community by Hake and allowed for the comparison of different classes by calculating a single gain value using the class average for pretest score and posttest score [95]. More recently, it is common for researchers to define normalized learning gain as displayed in Equation 2.1, where each individual student has a score and the average of gains is compared between groups [153]. While this definition of nlg may emphasize performance improvements for students starting with a higher pretest score (in an example test with five items, a student improving from .00 to .20 has an nlg of .20, whereas a student improving from .80 to 1.00 has an nlg of 1.00), it does provide each individual with the same potential improvement score, accounting for various starting scores. Many of these statements are difficult to understand objectively without considering the improvement relative to a given individual. It is tough to objectively judge how likely it is for an individual to make an improvement from pretest to posttest without knowing the population and without knowing the challenges that each individual faces. Because of this, we find it important to measure improvements relative to an individual's baseline performance using matched data, rather than comparing posttest scores between groups. Though students are likely to make some improvement between pretest and posttest, it is possible for students to have a lower posttest score than their pretest score. One variant for representing this loss is to define nlg as $score_{\text{post}}(i) - score_{\text{pre}}(i)/score_{\text{pre}}(i)$ when the posttest score is lower than the pretest score, measuring the loss out of the total potential loss instead of the total potential improvement.

Teachers' assessments of learning improvements are highly valuable as they can often capture qualitative improvements for individual children that are not measured by a posttest. However, they are hard to obtain automatically and are often not feasible to collect for a large number of students in user studies designed to evaluate the effectiveness of a tutoring system. Though each of these measures have drawbacks, we chose to compare normalized learning gain between experimental groups in the studies we describe in the following four chapters. We did this because it is a unified metric that accounts for individual pretest scores and can be compared directly between groups using parametric or non-parametric statistical tests, depending on the distribution of a particular dataset. Because learning gain is a measure of improvement, we always exclude participants with a perfect starting score, as they have no potential improvement to make, which does not fit with the traditional meaning of nlg for other participants. Though we use normalized learning gain (or its variant) to compare experimental groups, we typically also attempt to demonstrate that the average pretest score of the groups are not significantly different, as well as look within groups at paired differences between test scores to understand which groups were able to make significant test score improvements.

- *Time to Complete Problems*: ITS systems often attempt to minimize the average time required for a student to complete problems correctly [30]. While this is straightforward to measure, a low time to complete problems does not always indicate a successful tutoring interaction. Students who can complete problems quickly may be finding the problems unengaging if they have already mastered the content. Other systems use time to complete problems as a measure of efficiency, using contextual information to interpret when intervention is required [37].

- *Time Spent Off Task*: Some tutoring systems capture the amount of time the learner spends off-task from the main learning task. This deals with user engagement, and assesses how effective the system is in maintaining engagement. This is difficult to measure, as observable behavior (for example, staring off into space) may or may not correlate with being on-task. Furthermore, it may differ greatly between students, and may also indicate other affective states such as boredom or frustration as well [197]. ITSs have focused on building models that can detect off-task behavior, relying only on the student's logfile data to determine when a student may be engaged in behavior that does not involve the learning task at hand [19].

- *Emotional Expressions*: Because of the importance of emotion and affect during learning, tutoring systems benefit from being able to understand what affective facial expressions and emotions arise during tutoring interactions. The occurrences of these behaviors are hard to detect automatically, so often video-coding analysis is required for identifying these behaviors. Analyzing video-coded data can help identify what affective reactions were present during an interaction, but does not allow an autonomous system to make use of this information in real-time. In order to build a tutoring system that can respond to these states online, some systems have tried to automate the process of measuring affect and emotion during learning using various sensors including facial analysis software [38, 87, 202], posture detection and pressure sensing [69], and prosody detection [146].

- *Perception of the Interaction or System*: Questionnaires involving Likert scales are often used to evaluate user perceptions of a tutoring system. This is typically more common for tutoring systems that include a pedagogical agent, as researchers are interested in understanding how students perceive various types of tutoring agents. For embodied robot systems, many studies have measured a user's perception of the robot by filling out subjective questionnaires that typically ask the user to evaluate the robot along several dimensions, such as animacy, and perceived likeability. Two examples of questionnaires like this are the Godspeed questionnaire [25] and the RoSAS scale [41].

2.3 Robots in Education

Though several ITSs have been successful in a variety of tutoring settings, learning is a process that is highly individualized and can benefit from social interaction [88, 164, 231]. Physically present robot tutors may afford more engaging interactions, with their abilities to interact with the physical space around a student, and provide embodied behaviors such as gesturing during teaching. Researchers in the field of HRI have begun to explore the use of robots in educational settings, and much of the more recent work involves using physically embodied robots as tutors for children, due to positive perception of robots by children [110, 209, 217]. In the following sections, we cover the current field of research on robots for education and describe state of the art systems in robot tutoring.

2.3.1 Why Robots? Considering Physically Embodied Tutors

As virtual agents offer some of the same advantages as tutors as physical robots but do not come with the complications of external hardware and maintenance, it is important to consider why the field of HRI wants to explore using physical robots in educational settings.

Robots are a natural choice when the material to be taught requires direct physical manipulation of the world. For example, tutoring physical skills such as handwriting [43, 100, 151] or basketball free throws [148] may be more challenging with a virtual agent, and this approach is also taken in many rehabilitation-focused or therapy-focused applications (e.g., [75]). Additionally, certain populations may require an embodied system. Robots have already been proposed to aid individuals with visual impairments [129] and for typically developing children under the age of two [203] who show only minimal learning gains when provided with educational content via screens [184].

Physical robots are also more likely to elicit social behavior from users that are beneficial to learning [112]. Robots can be more engaging and enjoyable than a virtual agent in cooperative tasks [119, 126, 227], and are often perceived more positively [132, 144, 173, 227]. Perhaps most importantly for tutoring systems, physically present robots yield significantly more compliance to its requests, even when those requests are challenging, than a video representation of the same robot [18].

In addition, physical robots enhance learning and impact later behavioral choice more substantially than virtual agents. Compared to instructions from virtual characters, videos of robots, or audio-only lessons, robots produce more rapid learning in cognitive puzzles [143]. Similar results have been demonstrated when coaching users to select healthier snacks [173] and when helping users to continue with a six-week weight-loss program [120]. A comprehensive review [144] concluded that the physical presence of a robot leads to positive perceptions and increased performance when compared to virtual agents, or robots displayed on screens.

2.3.2 Robot Roles in Education

Robots are typically used in educational settings in the role of a tutor or teacher. However, they can also take on the role of a peer or novice. As a tutor, robots can take on similar roles to virtual agents or other ITSs, providing hints, tutorials, and other feedback and assistance that provides curricular support. Most of the studies conducted involving educational interactions with robots cast the robot into the role of a tutor that provides support during learning and often facilitates the tutoring interaction [115, 116] They are usually studied in one-on-one settings, as this setup more readily allows for the robot to personalize their tutoring behaviors, but some tutoring robots have been used with larger groups to deliver lectures or small group interactions [4, 138, 233].

Some work has explored the idea of using the robot as a peer learner. Particularly for young children, a peer learner has the advantage of being less intimidating than a teacher or tutor, and provides an engaging companion to share the experience of learning for the student. Some work in one-on-one educational scenarios have involved children playing games or completing an activity with a robot, such as a storytelling exercise [125, 135]. In one study, when a peer robot was compared to a tutor robot, students paid more attention to learning tasks and gave faster responses [235]. The idea of a companion robot that serves as a peer learner may offer motivational support to the student, which is particularly relevant for young children in learning environments [149].

The idea of casting the robot into a novice learner has also been explored. This allows the student to take on the role of the teacher, which is called *learning-by-teaching*. This is a well-known paradigm in the education literature and is also called the Protégé effect [44]. When children take on the role of a teacher for a novice learner, they typically bolster their confidence as well as improve their mastery of the material. One example of this was the use of the Care-Receiving Robot (CRR), which was a teachable robot used in a language learning setting, in which the robot would deliberately make mistakes and rely on the children to correct the errors [219]. This helped the children improve their own vocabulary skills, and the engaging nature of CRR led to the release of a commerical platform based on the idea of using the robot as a novice learner [218]. Another notable example involves children improving their handwriting skills by teaching a robot to improve its handwriting skills, leading to improved performance from the students [100].

2.3.3 Robot Platforms

As we described in Section 2.3.1, the physical presence of robot tutors are often cited as the reason for their ability to draw out social behaviors and responses in users that are important for learning. Despite this, it is unclear whether certain qualities or attributes about the robot's physical appeareance contributes to these behaviors, such as increased engagement or compliance. Studies investigating the efficacy of robot tutors do not focus on the impact of particular robot platforms, but rather focus on the contribution of the robot's behavior mechanisms in various educational scenarios. Here we describe popular robot platforms that have been used in research involving robots for education (Figure 2.1).

The most popular robot platform used in user studies involving robots in educational settings is the Nao robot, which is a 54cm tall humanoid robot developed by SoftBank Robotics [1]. This robot has arms, legs, a torso, and a head, and can be programmed to walk, gesture, and pan and tilt its head. The majority of research studies involving robots in

(a) (b) (c) (d)

Figure 2.1: Examples of robot platforms used in tutoring settings. Typically, smaller robots that can fit easily on a table in front of a child are used in tutoring applications for children. The following robots are pictured: (a) Nao [1] (b) Keepon [127] (c) iCat [221] (d) Tega [207].

educational settings utilize the Nao robot likely because of how easy it is to program and use, its prevalence in research labs as one of the few robot platforms that has technical support and available repair, and its relatively cost-effective price point for a research platform. Though it can be programmed to walk, most tutoring studies that use Nao do not use the legs for mobility, and typically have the Nao in a sitting or crouching position.

Another platform that has been used in foundational work investigating robot tutoring [142, 143] is called Keepon [127]. This is a much smaller robot (15cm tall) that is yellow, has a snowman shape with no arms or legs, and is limited to four degrees of freedom (pan, roll, tilt, and bop). Though the Keepon robot is much more limited in terms of motion capabilities compared to the Nao, it is a much more cost-friendly alternative, as the original version was later manufactured as a toy for children and has been successfully used as a programmable research platform with low-cost modifications [3, 138, 139].

Finally, we see a large number of other robots used in studies involving educational settings. Some notable examples include the iCat robot, which is a table-top robot that can mechanically render facial expressions [221], and both DragonBot and Tega, which are Android-based robots that use smart phones to display and animate the robot's face [207]. Though not always the case, tutoring robots for children are often smaller, table-top robots that are positioned near the student and do not change location during the course of a one-on-one tutoring session. Studies have not typically focused on directly comparing different robot platforms due to the practical considerations and difficulties of doing so, as the choice of robot in each study typically depends on the availability of certain platforms in different research labs and countries. Even for researchers that have multiple platforms, it is difficult to directly compare between different robots due the high variance in each robot's features and capabilities. For example, do we compare a Nao robot that gestures to a Keepon robot? Or do we instead compare a Nao robot that never gestures to a Keepon robot since it does not have the ability to use gestures? It is challenging to assess the benefits of one platform over another due to this mismatch in comparability.

2.3.4 Diverse Applications of Robot Tutors

Based on the advantages of physically present robot tutors, much work has focused on demonstrating the use of robots in education in a variety of different domains. Robots have been used successfully in tutoring interactions involving many traditional learning subjects, such as math [114], reading [158], and language learning [87, 116, 206]. Robots have also been used to play cognitive games, such as chess, with children, acting as an engaging companion [135]. Recent work has also explored the use of robot tutors and coaches that support students in improving more physical skills, such as handwriting and basketball free throws [100, 148].

Because of the increased engagement that children typically experience with robot companions, non-traditional application domains have also benefitted from the use of robot tutors. For example, a social robot companion was used to teach young children about nutrition and healthy food choices over several sessions [209]. Other work has explored using multiple robots to teach children about the consequences of bullying, acting out scenarios that would be challenging for students to act out themselves [139]. Physical robots are also being used in conjunction with virtual avatars in new interaction paradigms used to support the learning of sign language for deaf infants [203].

Aside from specific skills and domains, robot tutoring systems, like ITSs, should also be exploring how to teach children more general problem-solving and monitoring strategies so that they can foster self-efficacy in students and help them become independent, academically-confident learners. Though this area in robot tutoring is currently underexplored, one body of work has started to investigate how we can use social robot tutors to foster self-regulated learning (SRL) skills in children [107, 108]. They demonstrated that a robot tutor that uses an open-learner model (OLM) and scaffolding could effectively help students build skills that involve self-monitoring, goal-setting, and help-seeking over several weeks [108].

2.3.5 Challenges in Building Effective Robot Tutors

There are a number of challenges in using technology to deliver content in education. Using a social robot adds to this set of challenges due to the robot's presence in the social and physical environment and due to the expectations the robot creates in the user. The social element of the interaction is especially difficult to automate: while robot tutors can operate autonomously in restricted contexts, fully autonomous social tutoring behavior in unconstrained environments remains extremely challenging.

Sensing the Learner

Perceiving the social world is a first step toward being able to act appropriately. Robot tutors should not only be able to correctly interpret the user's responses to the educational content offered, but should also interpret the rapid and nuanced social cues that indicate task engagement, confusion, and attention. While automatic speech recognition and social signal processing have improved in recent years, sufficient progress has not been made for all populations. Speech recognition for younger users, for example, is still insufficiently robust for most interactions [118]. Instead, alternative input technologies such as a touchscreen tablets or wearable sensors are used to read responses from the learner and though potentially less effective, can be used as a proxy to detect engagement and to track the performance of the student [28, 178, 216]. Robots can also utilize explicit models of disengagement in a given context [139] and employ strategies such as activity switching to sustain engagement over the interaction [53]. Computational vision has made great strides in recent years, but still falls short when dealing with the range of environments and social expressions typically found in educational and domestic settings. Many of the social cues that should be sensed are extremely subtle, differ between users, and even change depending on whether the learner is alone or in a group [139]. While advanced sensing technologies for reading gesture, posture and gaze [27, 140] have found their way in tutoring robots, most social robot tutors continue to be limited by the degree to which they can accurately interpret the learner's social behavior.

Robot Behaviors

Armed with whatever social signals can be read from the student, the robot must choose an action that advances the long-term goals of the educational program. However, this can often be a difficult choice even for experienced human instructors. Should the instructor press on and attempt another problem, advance to a more challenging problem, review how to solve the current problem, offer a hint, or even offer a brief break from instruction? This may not only depend on the current cognitive and affective state of the student, but may also be time dependent based on the student's past performance and the history of what support has already been given to the student. There are often conflicting educational theories in human-based instruction, and whether or not these same theories hold when considering robot instructors is an open question. While these choices are also present in non-embodied intelligent tutoring systems (ITS), the agentic nature of robot tutors often introduces additional options and, at times, complications. Different robot roles will likely require different behavior repertoires and possibly different action selection rules as well. Choosing an appropriate emotional support strategy based on the affective state of the child [136] and selecting robot responses based on the child's affect [87] have both been shown to improve student learning gains. Combining these actions with appropriate gestures [102], appropriate and congruent gaze behavior [103], expressive behaviors and attention-guiding behaviors [200], and timely non-verbal behaviors [115] also positively impact student recall and learning. However, merely increasing the amount of social behavior for a robot does not necessarily lead to increased learning gains, as certain studies have found that "too much" social behavior may be distracting [114]. Instead, the social behavior of the robot must be carefully designed in conjunction with the interaction context and task at hand in order to enhance the educational interaction.

Personalization in Robot Tutoring

Finally, substantial research has focused on personalizing interactions to the specific user. Within the ITS community, computational techniques such as dynamic Bayesian networks, fuzzy decision trees, and hidden Markov models are used to model student knowledge and learning [32, 51, 213]. Similar to non-embodied tutoring systems, robot tutors use these same techniques to help tailor the complexity of problems to the capabilities of the student, providing more complex problems only when easier problems have been mastered [86, 142, 206]. Several robot tutoring systems have also used approaches based on BKTs [59,142,206]. Providing hints based on a BKT model of skill estimation improved learning gains on a puzzle-solving task for adults [142]. Additional work has successfully used a BKT-based approach to tutor language skills for adults and children [59, 206].

In addition to the selection of personalized curricula, robotic tutoring systems often provide additional personalization to support the individual and their interaction preferences. Even straightforward forms of personalization, such as using a child's name or referencing personal details within an educational setting, can enhance user perception of the interaction and is an important factor in maintaining engagement within learning interactions [99,106]. Other effective personalization strategies have been explored to maintain engagement during a learning interaction by using reinforcement learning to select the robot's affective responses to the behavior of children [87]. A field study showed that students who interacted with a robot that demonstrated three types of personalization (non-verbal behavior, verbal behavior, and adaptive content progression) showed increased learning gains and sustained engagement when compared to students interacting with a non-personalized robot [26].

While progress has been made in constituent technologies of robot tutors —from perception, to action selection and production of behaviors that promote learning — the integration of these technologies and balancing their use to elicit prosocial behavior and learning still remains an open challenge.

2.3.6 Long-Term Tutoring Interactions

In order to evaluate robot tutors as effective learning tools in the educational domain, it is critical to study their impact in tutoring settings that are longer than a single session. Many of the foundational results showing the value of robot tutors are based on studies conducted in single sessions, or short-term interactions. As learners change over time, robot tutors must also adapt to fit the needs of individual students over time. A few more recent bodies of work have looked at robot tutoring interactions in long-term studies. Some early studies investigated whether putting robots into classrooms for long periods of time would impact attitudes and progress of the students in the classroom [110,217,219]. Tanaka et al. explored how children interacted and behaved toward a robot that was brought into a classroom for 27 different sessions over five months, finding that children treated the robot more like a peer than a toy by the end of the five months [217]. Similarly, an autonomous robot placed in the classroom of a group of young toddlers for two weeks led to improved vocabulary use of toddlers [160]. Leite et al. deployed a robot tutor as a chess companion that provided empathic support to children, and the robot adapted its empathic responses to the child over the course of five separate sessions [136]. Gordon et al. also investigated using a reinforcement learning approach to selecting appropriate affective responses to students in a language learning setting that spanned eight separate tutoring sessions spaced out over two months [87]. These efforts to evaluate the effectiveness of robot tutors in longer-term settings represent important progress towards evaluating the feasibility of using robots in natural environments for much longer periods of time, such as months or years.

2.4 Summary

In this chapter, we reviewed the state of the art in robots for education. We discussed relevant techniques and systems from the field of Intelligent Tutoring Systems and then presented the current issues, challenges, and progress that has been made thus far in the field of using robots in education. In the following chapters, we will refer to background sections from this chapter to demonstrate how our novel contributions relate to existing work in robots for education. The original work in this dissertation focuses on designing and modeling robot behaviors that can be used to enhance the effectiveness of tutoring interactions for children.

Chapter 3

Personalized Break Timing in Robot-Child Tutoring*

Engagement and attention are critical components to successful learning [77]. If a student is not paying attention, it is unlikely that he or she will be learning effectively during a tutoring interaction. Maintaining engagement within a tutoring interaction then becomes an important piece of effective learning scenarios. While there might be several approaches to track engagement over time [92, 139, 216], feasible ways to augment a robot's tutoring behaviors to keep a student engaged during learning must be considered. Constantly trying to maintain engagement over a long interaction may not be feasible, especially for younger students of varying abilities and levels of focus. For example, even if a student is continuously receiving problems at the right level of challenge, their attention may wane and render the tutoring that follows ineffective. Knowing when a student is feeling cognitively overwhelmed and providing a break that is unrelated to the tutoring task at hand then becomes a practical way to maintain engagement and potentially repair it over longer, more cognitively taxing interactions.

In this chapter, we explore personalization mechanisms robot tutors can employ to maintain engagement over the course of an extended tutoring session. Specifically, we investigate

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personalized timing strategies for providing breaks to young learners during a robot tutoring interaction. We conducted a field study in which participants completed a lengthy tutoring session with a robot, in which the robot provided breaks to the child throughout the interaction. We varied the timing of when these breaks occurred and compared a fixed timing strategy with two personalized strategies. Our results show that the personalized timing strategies promote learning more effectively both during and after the tutoring interaction as compared to the fixed strategy. This chapter also highlights one of the main themes of this work: personalized robot behavior that responds to critical components of student learning can positively impact learning outcomes.

3.1 Introduction

One crucial aspect in a learning interaction is the student's engagement and attention, particularly for younger learners who often have short attention spans. The attention spans of children can be as short as five minutes in a learning interaction [169], and the capacity for sustained attention only develops significantly between age 11 and adulthood [154]. Addressing this need in learning interactions for young students is extremely important. A common practice in education to accommodate the short attention spans of children during learning is to provide them with non-task breaks for cognitive rest. Research has suggested that breaks are beneficial and provide needed cognitive rest during learning [14, 145]. Moreover, interspersing non-task breaks into an extended learning task may reduce interference and strengthen the learner's performance [62, 220]. Therefore, to effectively promote learning for younger students, robots need to intelligently provide necessary breaks over the course of a learning interaction (Figure 3.1).

Break timing—when to provide a break—is particularly important, as it allows students to have needed cognitive rest at the right time. In a traditional learning environment, such as a classroom, breaks are usually taken at regular intervals. On the other hand, in a tutoring interaction, breaks can take place at times personalized to an individual. Breaks can be positive reinforcers for desired behavior (e.g., improved learning performance). Alternatively, breaks can be an opportunity for students to refocus after experiencing a decline in

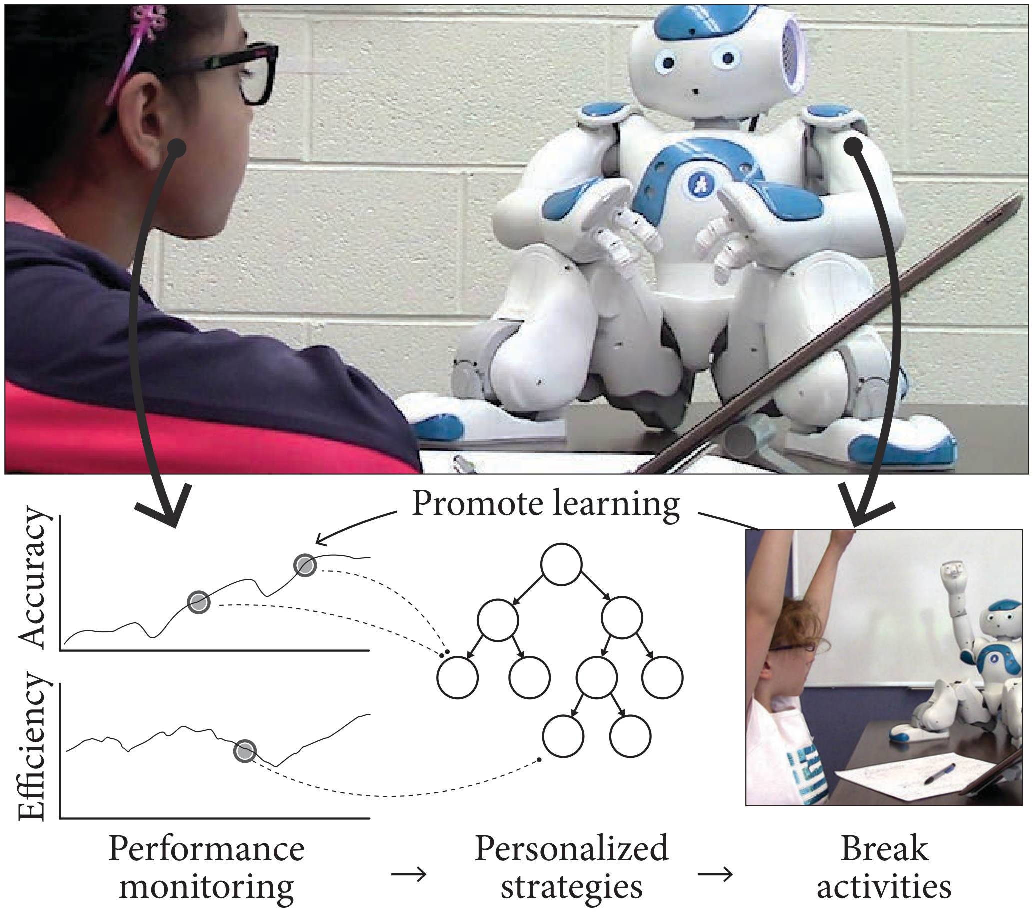


Figure 3.1: We studied personalized strategies for providing breaks to promote children's learning during one-on-one tutoring interactions with a robot.

learning performance. In this chapter, we explore how a tutoring robot can provide breaks following a personalized schedule based on learning performance and seek to understand how such personalization might influence student learning outcomes.

Both choosing *what* behaviors and *when* to provide them are important components of maintaining engagement over time. In this study, we design a set of engaging break activities for the social robot to provide to the children and focus our investigation on whether personalizing the timing of these breaks to student performance benefits learners during the interaction. We develop two personalized timing strategies inspired by real-world educational practices that are responsive to individual performance during the tutoring session.

3.2 Background

In this section, we present relevant background literature showing that breaks can contribute to effective learning, and offer evidence about different ways to provide these breaks. We then briefly recap related work from Chapter 2 involving personalization and maintaining engagement in human-robot interaction.

3.2.1 Non-task Breaks and Learning Gains

Breaks—pausing the current task to rest or to work on a different task—are beneficial for cognitive- and attention-loaded tasks. For example, during cognitive work involving recognition memory, breaks can foster achievement gains [220]. Furthermore, breaks of varying lengths can have restorative effects on reaction time during an auditory response task [145]. Accordingly, breaks play an important role in learning, a complex activity demanding the learner's cognitive attention. Learning can be particularly challenging for children, as their attention spans can be quite short, making them susceptible to distractions during learning [62, 169]. In support of this need, a common educational practice is to provide breaks throughout a school day at scheduled times. Primary schools in various countries that allow children to take 10- to 15-minute breaks every 40 to 45 minutes of classroom instruction report increased attentiveness after the breaks, indicating the importance of breaks during learning [166,167]. However, limited time and resources during a school day necessitate that all children receive these breaks at the same time. Each individual has different learning needs and varied attention spans, suggesting that these non-task breaks may be most useful if provided at the "right" time.

Alternative educational practices suggest that non-task breaks could be provided in ways more personalized to each individual. For example, *success-based rewards* can enhance performance [170]. This provides evidence for one design of a personalized timing strategy for breaks in which breaks are used as success-based rewards for students demonstrating learning improvement. This strategy uses these breaks as a positive reinforcer for desired performance improvements. Another classroom practice, *positive time-out*, informs a second design of a personalized timing strategy to prevent or mitigate negative emotions. "Positive time-out" allows a child to take a brief break to avoid outbursts caused by affective reactions such as frustration [162]. Students can experience a wide variety of negative emotions during learning, often due to poor performance, and these can have a further negative impact on learning gains [165]. Thus, this strategy provides breaks during moments of potential negative emotion to enhance learning gains.

3.2.2 Maintaining Engagement in HRI

Though we are the first to investigate personalized break timing in robot-child tutoring, researchers have been looking at the role of engagement within many types of human-robot interaction [42,139,183,201,211,216]. Because engagement is often thought of as a precursor to effective interaction, several other studies have studied the how robots can specifically engage children [33,54,64,139,187,235]. As detailed in Chapter 2, much of the work involving attention has focused on finding approaches to detect engagement or disengagement during an interaction [27, 42, 92, 139, 140, 183]. For example, Leite et al. built data-driven classifiers to detect disengagement in groups of children versus individual children [139]. Other recent work by Lemaignan et al. defined an online method of assessing a child's attention during a learning interaction [140]. Szafir and Mutlu showed that a robot can monitor attention in real-time based on EEG sensor data and use this information adaptively to improve student recall ability [216]. Rather than elaborated estimation of attentional state, our work uses performance-based features during learning to estimate measures of engagement.

Specifically within an educational setting, researchers have investigated how to engage students through the use of personalization within the interaction [87, 142, 204, 229]. Some work has focused on providing some aspect of content personalization, on the premise that students stay more engaged when presented with material at the right level of challenge. This is similar to the approach most commonly found in ITS literature, which tries to trace student performance on a given skill using a technique called Bayesian Knowledge Tracing and typically advances content difficulty level after a certain mastery threshold is reached [55]. Other work has looked at re-engagement strategies, as an effective robot tutor should attempt to repair student attention if it is lost [37, 137, 216]. One study showed that a robot can re-engage users by employing socially supportive verbal phrases [37]. In addition, Leite et al. used trained models of disengagement to detect when a group of students was off-task and explored intervention strategies on how to repair the group's engagement, finding that targeted interventions to an individual in the group may be more effective than general interventions addressing the whole group [137,139]. The study detailed in this chapter focuses on non-content personalization in a one-on-one tutoring setting; we specifically investigate how the personalization of break timing to sustain engagement throughout an educational interaction for children impacts learning outcomes.

3.3 Robot Tutoring System

In this section, we provide an overview of our design of an autonomous robot tutoring system (Figure 3.2). We also present the personalized strategies and support mechanisms implemented for our investigation of how the robot tutor may personalize break timing to promote learning.

3.3.1 System Overview

Our robot tutoring system consists of three main software components—*performance monitor*, *activity scheduler*, and *content selector*. The performance monitor is responsible for continuously tracking the student's learning performance, particularly his or her accuracy and efficiency at solving the educational problems presented on a tablet. The activity scheduler utilizes the collected performance information as well as personalized strategies to decide when to provide a non-task break activity during the student's learning interaction. The content selector uses the student's accuracy performance to selectively pick subsequent educational content that matches the student's mastery of the learning material. Specifically, the content selector decides the suitable difficulty level of the problems presented to the student. We use the Nao robot in our system to provide tutoring support.

3.3.2 Personalized Strategies

In this work, we explore three strategies for choosing when to provide a break during a tutoring interaction. The implementation of these strategies will be discussed in Section

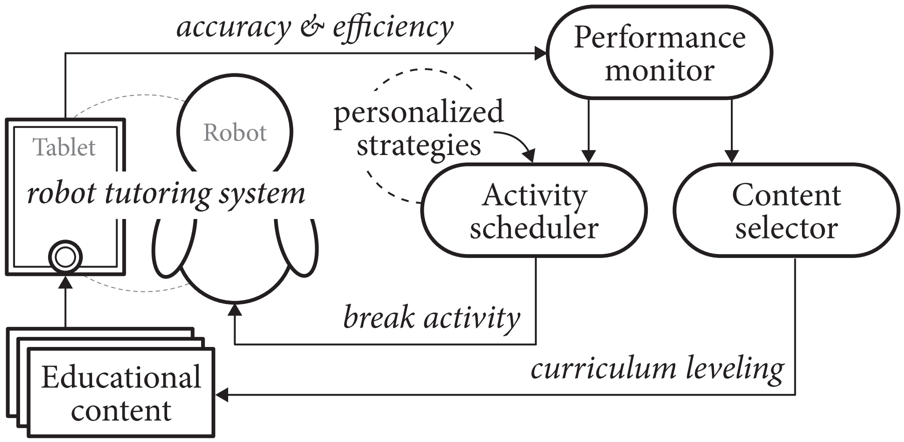


Figure 3.2: System architecture of our robot tutoring system.

3.4.2. Below, we describe the design rationale of these strategies.

Fixed strategy—This strategy provides breaks to students on a fixed schedule at regular intervals, reflecting the classroom practice that all children receive breaks at specified times rather than times particular to the individual.

Reward strategy—This strategy provides breaks as a reward after good performance as informed by the educational practice of "success-based rewards" [170]. This strategy seeks to postively reinforce desired learning improvement.

Refocus strategy—This strategy seeks to interrupt negative behaviors, such as distraction, during learning by providing a break when a drop in performance is detected. This design is informed by the educational practice of "positive time-out" [162], providing a student with the opportunity to refocus by taking a break from the task at hand.

3.3.3 Support Mechanisms for Tutoring

In addition to the personalized strategies, our system also implements several basic support mechanisms, including providing necessary information on the tablet application and exhibiting engaging robot behaviors, to facilitate tutoring interactions with young learners. All behaviors described in this section apply to all students regardless of the assigned conditions for the user study described in Section 3.4.2. At the start of a tutoring session, the robot greets each student and conducts a small, interactive lesson on an educational topic. After the lesson, the robot presents a series of questions on the taught topic for the student to practice. We carefully designed robot behaviors to give the students the impression that the robot was responsible for facilitating the learning interaction. For instance, the robot looks at the students when speaking and looks at the tablet while they work on practice questions. The robot also uses gestures throughout a session, often extending an arm towards the tablet to invite students to direct their attention towards it.

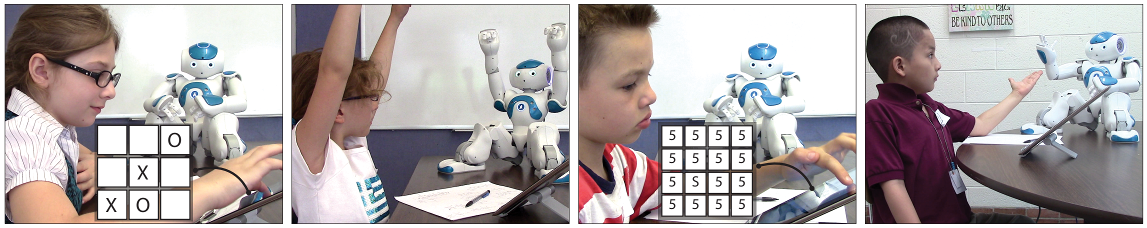
The content selector chooses each practice question from a bank of problems with multiple difficulty levels to accommodate a variety of learners. All students start with the lowest level of questions available and can only advance to subsequent levels after demonstrating a specified level of mastery. The robot provides feedback on whether an answer is correct or incorrect after each individual problem. If the answer is incorrect, the robot also provides general feedback about how to solve the problem, while the tablet displays the associated worked-out solution. Moreover, the tutoring application helps manage the flow of the tutoring interaction by providing buttons on the screen that allow the student to initiate the presentation of the next problem and disabling buttons displayed on the tablet while the robot verbally delivers tutoring information. Upon reaching the allotted time, the robot congratulates the student for completing a session.

3.4 Methods

In this section, we describe a user study investigating the effects of different personalized strategies for determining break timing, as employed by the robot tutoring system described in Section 3.3, on students' learning outcomes.

Table 3.1: Examples of practice math problems for each of the concepts and difficulty levels given to the students.

	C1: Multiplication	*C2: Parentheses*
Level 1	$2 + 8 \times 2$	$5 \times (2 + 4)$
Level 2	$5 + 6 \times 1 + 6 \times 4$	$6 + (2 + 6) \times 7$
Level 3	$31 + 5 \times 9 - 7 \times 4$	$8 + 8 \times (1 + 5) + 3$



(a) Game play: tic-tac-toe (b) Physical exercise: stretch activity (c) Refocusing activity: spot-it (d) Relaxation: breathing activity

Figure 3.3: Four break activities that were received during the tutoring session. Each break activity lasted about two minutes.

3.4.1 Evaluation Context

The user study was contextualized in a tutoring interaction in which children learned about mathematical concepts and then practiced these concepts by completing problems with the robot, thereby creating a repetitive learning interaction. Students completed a 40-minute learning interaction to approximate the length of a scheduled class period during an elementary school day. We present the educational content below, and provide a description of the non-task break activities that were used across all experimental conditions.

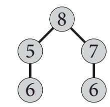
Educational Content

We chose to teach two math concepts involved in "order of operations" that the students had not previously learned in their classrooms. Specifically, the students learned that multiplication comes before addition and subtraction (C_1: *multiplication*), as well as the concept that parentheses come before all other operations, including multiplication (C_2: *parentheses*). We designed practice problems for each of the two concepts for three difficulty levels; examples are provided in Table 3.1. Students had to complete a minimum of ten questions per difficulty level. Moreover, they needed to achieve 70% accuracy to be considered to have mastery of that difficulty level before advancing to the next level.

Break Activities

Throughout the tutoring session, the robot provided the students with brief breaks from the learning activity. We designed four break activities that leveraged the physical and social nature of the robot, including game play, physical exercise, a refocusing activity, and

Table 3.2: Break triggering mechanisms for each condition. Percent changes from history to window data for accuracy and timing are represented by $\Delta Accuracy$ and $\Delta Time$, respectively. Overall history accuracy is denoted by $\mathbf{a}_{history}$. N is the number of times each type was triggered. The conceptual decision tree shows the order in which the triggers were considered.

Condition	Trigger type	Description	Implementation	N	Conceptual decision tree
Fixed	1	Fixed schedule	Six minutes elapsed	39	N/A
Reward	2	Accuracy improvement	$\Delta Accuracy \geq 20\%$	43	
	3	Efficiency improvement	$\Delta Time \leq -20\%$, $\mathrm{a}_{history} \geq 70\%$, $\lvert\Delta Accuracy\rvert \leq 20\%$	0	
	4	Good performance over time	$\{ \lvert\Delta Accuracy\rvert , \lvert\Delta Time\rvert \} \leq 20\%$ for 10 questions, $\mathrm{a}_{history} \geq 70\%$	1	
Refocus	5	Efficiency drop	$\Delta Time \geq 20\%$, $\lvert\Delta Accuracy\rvert \leq 20\%$	14	
	6	Low performance over time	$\{ \lvert\Delta Accuracy\rvert , \lvert\Delta Time\rvert \} \leq 20\%$ for 10 questions, $\mathrm{a}_{history} < 70\%$	2	
	7	Timing drop, indicating guessing	$\Delta Time \leq -20\%$, $\mathrm{a}_{history} < 70\%$, $\lvert\Delta Accuracy\rvert \leq 20\%$	15	
	8	Accuracy drop	$\Delta Accuracy \leq -20\%$	13	

relaxation, which all students could receive in the same order (Figure 3.3). Each activity lasted approximately two minutes and aimed to provide mental "rest" from the math-based task. The stretch and relaxation breaks were specifically designed to be two minutes long, whereas children completed as many rounds of tic-tac-toe and the visual focus activity as they could within two minutes. The robot engaged with the child during each activity; the robot played tic-tac-toe against the child, led the child in the stretch and relaxation exercises, and facilitated each round of the refocusing activity. Students were not informed in advance that they would be receiving breaks, thereby eliminating any initial expectation for breaks.

3.4.2 Experimental Design

We designed a between-subjects study involving three experimental conditions—*fixed*, *reward*, and *refocus*—that realized the three strategies described in Section 3.3.2. The only independent variable in this study was the timing of the breaks. Table 3.2 summarizes the implementation of the activity scheduler, listing the triggers that initiated breaks in the experimental conditions. Below, we provide detailed descriptions of the conditions and our implementation of the triggering mechanisms used in all conditions.

Fixed Condition

In the *fixed* condition, the robot provided a break at regular intervals for each student regardless of their real-time performance on the learning task. This design reflects the classroom practice that all students get breaks at the same time as everyone else, regardless of an individual's need for a break. Acknowledging the short attention spans of children [169], we implemented the fixed strategy by providing a break every six minutes, allowing most participating students to receive the four distinct breaks over the 40-minute session.

Reward Condition

The *reward* condition, as informed by the educational practice of "success-based rewards" [170], implemented the reward strategy as described in Section 3.3.2. In this condition, the robot provided a break to the user upon detection of substantial improvement during the session. The performance monitor measured learning performance using two quantities: the accuracy of the student in answering questions correctly, and the time it took for the student to complete each question. A local *window* of recent history (five questions) of user performance (see Figure 3.4) was kept for both accuracy data and timing data as the session progressed. After each question, the local window data was compared to the entire

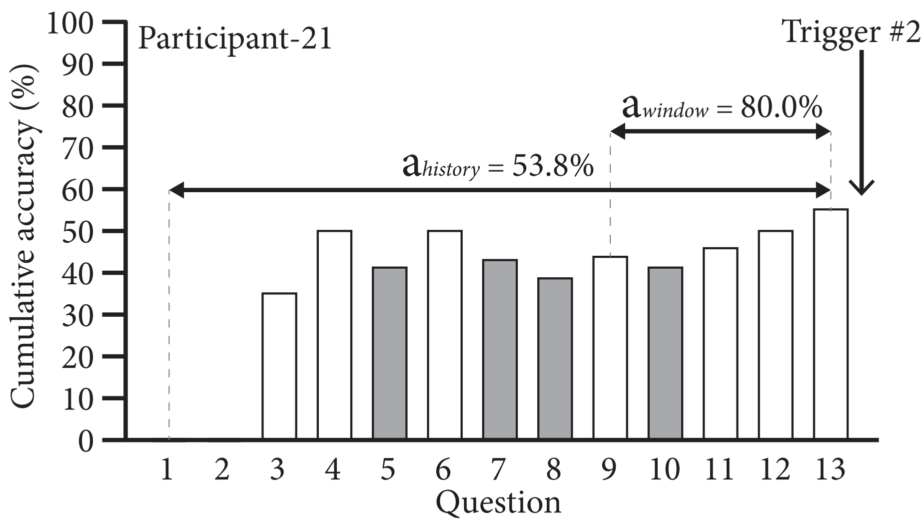


Figure 3.4: Sample user accuracy data showing how *window* and *history* values were calculated. The window size was five questions. Here, trigger type 2 was initiated because the percent change between $\mathbf{a}_{history}$ and $\mathbf{a}_{window}$ was greater than 20%. Gray bars represent incorrect answers.

history of data to understand whether there had been a performance increase in accuracy and efficiency (timing). The history data was reset when the difficulty level changed.

The implementation of the reward strategy can be represented conceptually as a decision tree (Table 3.2). First, the strategy considered increases in accuracy (type 2). Subsequently, the strategy would consider improvements in timing (type 3). Based on whether sizable changes (20%) occurred with the local windows of accuracy and timing as compared to the whole history, a break was given to the participant. If no substantial performance changes occurred for ten consecutive questions, but the participant's overall history of accuracy remained high (≥70%), the student received a break for performing consistently well (type 4).

Refocus Condition

The *refocus* condition, as informed by "positive time-out" [162], provided a break upon detecting performance drops. The implementation of this condition also relied on the performance monitor calculating a local window of accuracy data as well as timing data in the same way as previously described for the reward condition. The conceptual decision tree structure applies here, as well: we first considered drops in accuracy (type 8), followed by changes in efficiency as measured by time to complete each problem (types 5 and 7). If the drop in performance between the local window and the entire history was sufficient (20%), a break was triggered. If no sizable performance drops (20%) occurred but the participant's overall history of accuracy remained low (under 70%) for ten questions in a row, the student received a break for low overall performance over time (type 6).

3.4.3 Experimental Procedure and Setup

Both parental and child consent for each student was obtained prior to conducting this study. Additionally, children were informed that there were no negative consequences for stopping the interaction at any time. Participating students were removed from their classrooms one at a time for the duration of approximately one hour each. Students were first asked to complete a pretest, consisting of 12 questions, to assess their knowledge of the learning concepts. Free-response questions were used to prevent students from answering correctly due to guessing. After the pretest, students engaged with the robot in a 40-minute tutoring session. This session consisted of a short lesson from the robot, followed by a series of practice problems for students to complete. According to the experimental conditions, the robot provided corresponding breaks throughout the session. If more than four breaks were triggered in a single tutoring session, the break activities would repeat starting from the first one.

During the tutoring interaction, students sat at a table in front of the robot and the tablet (Figure 3.1). Each child interacted exclusively with the autonomous robot tutoring system during the session, requiring no input from the experimenter in the study room. After the tutoring session, students completed a posttest to assess their knowledge of the learning concepts. Both the pretest and posttest were the same length, including four questions of each of the three difficulty levels, and were identical except the order of the questions. Students also completed a brief questionnaire about their experience with the robot. Students were given pencils and stickers after completing the entire study and returned to their classrooms.

3.4.4 Measures

To explore how personalized break timing may impact learning outcomes, we employ three objective measures: (1) *learning gains*, (2) *efficiency* in problem solving, and (3) *accuracy* in problem solving. We define normalized learning gain (nlg) that captures the normalized difference between pretest and posttest scores for each student i:

$$nlg(i) = \frac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{1 - score_{\text{pre}}(i)} \tag{3.1}$$

Both the pretest and posttest scores are represented as accuracy scores calculated by dividing the number of questions answered correctly by the total number of questions. This nlg metric provides an index of improvement for each student, accounting for differing incoming knowledge levels.

In addition to learning gains, we seek to understand whether the break activities have any immediate effects on student performance in completing each problem. To this end, we calculate average efficiency and accuracy in solving problems, using a window of five problems, before and after each break. As breaks were initiated by different trigger types (Table 3.2), we assess the difference between performance before and after the breaks separately for each trigger type.

3.4.5 Participants

Forty students were recruited from elementary schools to participate in this study and were randomly assigned to one of three experimental conditions. Two participants were excluded from this data analysis due to non-compliance and technical problems during data collection, resulting in a total of 38 participants (13 females and 25 males). Among the 38 participants, there were 12, 14, and 12 participants in the fixed, reward, and refocus conditions, respectively. The participating students were in third grade; the average age was 8.53 years old (SD=.60). The groups were gender balanced, and there were no major differences found between the three conditions regarding age. Pretest scores for the three groups were: Fixed (M = .33, SD = .33); Reward (M = .18, SD = .28); Refocus (M = .25, SD = .18). A one-way ANOVA showed no statistical differences between the three groups, $F(2, 35) = 1.04$, $p = .363$, regarding the pretest.

3.5 Results

In this section, we first present findings characterizing how the robot tutoring system was used by students, to provide a basis for our further data analyses. We then present results on student learning gains and performance during problem solving (summarized in Figure 3.5). For all the statistical tests reported below, we used an α level of .05 for significance. We used non-parametric statistical tests when appropriate according to the distribution of the analyzed data.

3.5.1 Characterization of Tutoring Sessions

Participating students were from differing backgrounds and were not able to make homogeneous progress throughout the sessions. Across the three conditions, 52.6% of the students

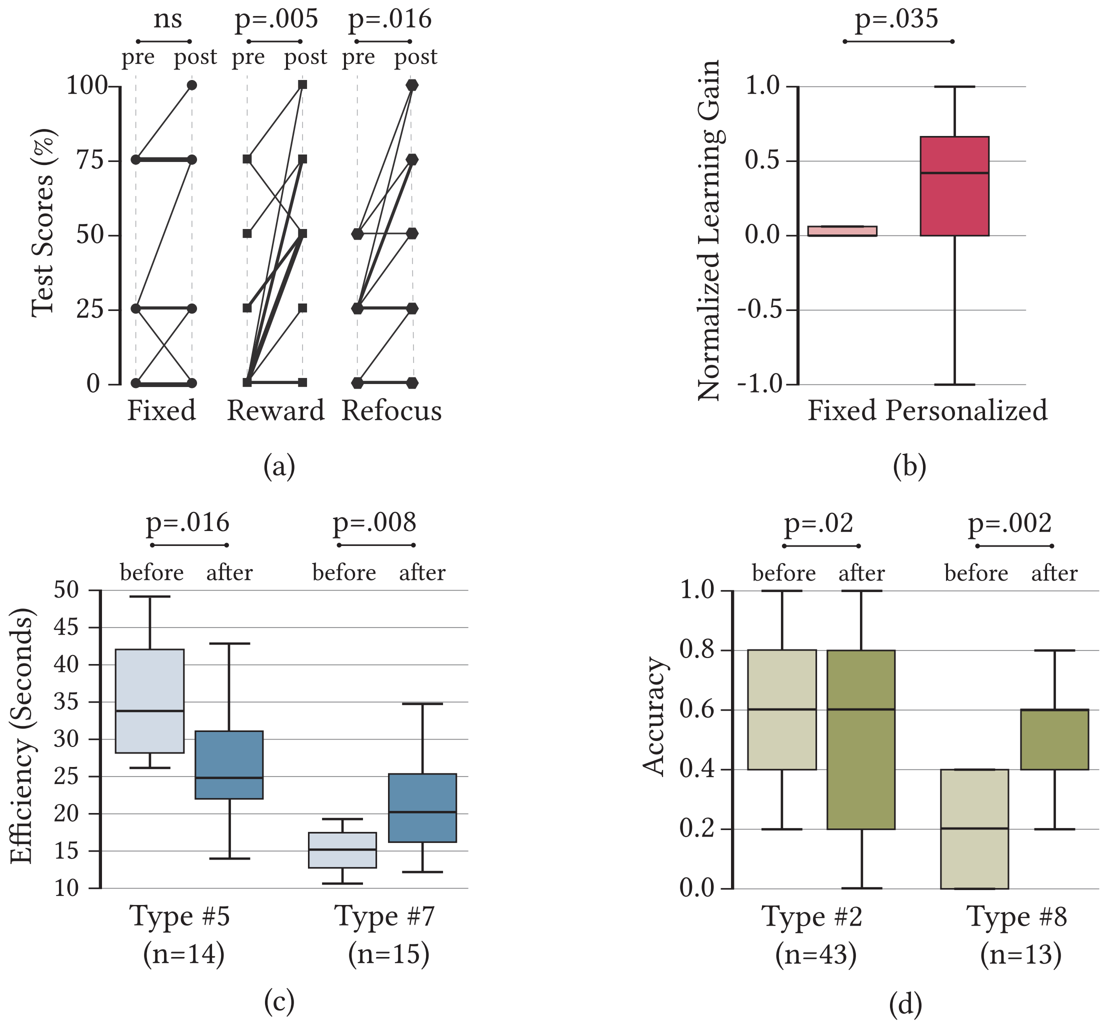


Figure 3.5: Results show the benefits of personalized break timing strategies: (a) Both the reward and refocus groups significantly improved in learning gains from pretest to posttest. Thicker lines indicate multiple participants with the same scores. (b) The personalization group (reward and refocus groups combined) improved significantly more than the fixed group, as measured by *nlg*. (c) Trigger types 5 and 7 significantly affected how much time students spent on problems before and after breaks. (d) Trigger types 2 and 8 significantly affected accuracy scores before and after breaks. For all boxplots, the darker line inside the box represents the median, and the extents of the box represent the first and third quartiles.

remained in level one for the entire session, 26.3% progressed to level two, and 21.1% were able to progress to level three. Due to such diversity, in the following section, we focus our analyses on student performance on level one assessment questions to draw fair comparisons. While students received a varying number of break activities according to the timing strategies, the average number of breaks provided per student was 3.74, and this was not significantly different across conditions, $F(2, 35) = .749$, $p = .480$. Moreover, the number

Table 3.3: Results of t-tests used to assess immediate effects of breaks on accuracy and efficiency by trigger type. (*) and (**) denote $p < .050$ and $p < .010$, respectively. Significant results are shaded in green.

Trigger type	Description	N	Accuracy			Efficiency (Seconds)		
1	Fixed schedule	39	Before	After		Before	After	
			M=0.50 SD=0.27	M=0.52 SD=0.35	$t(38)$=-0.387 p=.701	M=45.42 SD=26.68	M=42.39 SD=26.21	$t(38)$=1.212 p=.233
2	Accuracy improvement	43	Before	After		Before	After	
			M=0.62 SD=0.24	M=0.50 SD=0.33	$t(42)$=2.412 p=.02*	M=24.92 SD=10.39	M=25.04 SD=10.79	$t(42)$=-0.089 p=.929
5	Efficiency drop	14	Before	After		Before	After	
			M=0.54 SD=0.28	M=0.50 SD=0.37	$t(13)$=0.763 p=.459	M=35.33 SD=8.10	M=26.66 SD=8.38	$t(13)$=2.765 p=.016*
7	Timing drop, indicating guessing	15	Before	After		Before	After	
			M=0.51 SD=0.33	M=0.39 SD=0.28	$t(14)$=1.890 p=.080	M=16.85 SD=6.77	M=21.65 SD=7.56	$t(14)$=-3.064 p=.008**
8	Accuracy drop	13	Before	After		Before	After	
			M=0.22 SD=0.17	M=0.52 SD=0.28	$t(12)$=-3.987 p=.002**	M=38.28 SD=20.05	M=34.96 SD=16.90	$t(12)$=1.307 p=.216

of breaks received and normalized learning gain were not correlated for participants in all groups, $r(36) = .10$, $p = .540$ (Pearson correlation). Furthermore, not all types of triggers were initiated equally during the sessions. The number of times that triggers were initiated is summarized in Table 3.2. In the reward condition, trigger type 2 (accuracy improvement) was initiated most frequently, whereas type 3 was never initiated and type 4 was only initiated once. In the refocus condition, trigger types 5, 7, and 8 occurred at a comparable rate, while type 6 was only observed twice. Accordingly, we considered trigger types that were initiated more than twice, namely types 1, 2, 5, 7, and 8, in our analyses of the effects of each trigger type.

3.5.2 Learning Gains

As less than 50% of the students advanced past the level-one difficulty, we focused our analysis on level-one questions to understand learning gains on content that all students spent time practicing with the robot. To assess whether students improved their scores from pretest to posttest, we used Wilcoxon Signed-ranks tests, treating the test score as a within-subjects measure, to assess each student's learning gains over the course of the tutoring session. Figure 3.5 (a) shows each student's score on the level-one difficulty questions on both the pretest and the posttest, separated according to experimental condition. Students in the fixed condition had posttest scores (Mdn = 1.0, $IQR = 3.0$) that did not differ significantly from their pretest scores (Mdn = 1.0, $IQR = 3.0$), $Z = -1.134$, $p = .257$. For students in the reward condition, posttest scores (Mdn = 2.0, $IQR = 1.25$) were significantly higher than pretest scores (Mdn = 0.0, $IQR = 1.25$), $Z = -2.829$, $p = .005$. Posttest scores (Mdn = 2.0, $IQR = 2.0$) were significantly higher than pretest scores (Mdn = 1.0, $IQR = 1.5$) for students in the refocus condition as well, $Z = -2.401$, $p = .016$. These results together show that the students who received personalized break timing strategies, either *reward* or *refocus*, significantly improved their scores, while the fixed group did not. These results provide evidence indicating that the personalization of when to provide breaks during a tutoring interaction can positively impact learning.

Next, we compared normalized learning gains, nlg, between groups using a Kruskal-Wallis test. This analysis showed marginal difference in nlg between the different conditions, $H(2) = 5.086$, $p = .079$. To further understand the potential benefits of personalized timing strategies, we created a *personalized* group by combining the reward and refocus groups. We then ran a Mann-Whitney test comparing nlg between the fixed and personalized groups (Figure 3.5 (b)). This comparison showed that the normalized learning gain was significantly greater for the personalized group (Mdn = .41, $IQR = .69$) than for the fixed group (Mdn = 0.0, $IQR = .19$), $U = 89.000$, $p = .035$.

3.5.3 Immediate Break Effects

Besides overall learning gains, we were interested in whether certain trigger types provided immediate effects on efficiency or accuracy during the tutoring interaction. Thus, we compared average performance (both efficiency and accuracy) for the window of five problems before and after each break separately for each trigger type using paired t-tests. Results for this analysis are in Table 3.3. These comparisons were carried out for each distinct trigger type as we sought to understand how different timings of breaks (i.e., different types of trigger) might shape student efficiency and accuracy.

Efficiency in Problem Solving

Our analysis revealed that trigger types 5 and 7 had significant effects on how much time students spent on problems before and after breaks, as summarized in Figure 3.5 (c). Trigger type 5 was initiated when students' efficiency dropped while there were no sizable changes in their accuracy. Breaks triggered by type 5 improved students' efficiency significantly, as students spent significantly less time solving problems after the breaks as compared to the time they spent before the breaks. This result indicates that providing a break after this trigger may refocus the students, thus leading to improved efficiency in solving problems.

Trigger type 7 represented the situation where students' overall accuracy was not desirable, yet they spent less time on problems at hand, suggesting guessing on answers without investing time into each problem. Our analysis revealed that students spent significantly more time after breaks initiated by trigger type 7 than they did before. This increase in time spent on problems may suggest that after the breaks students were able to refocus their attention on the math task. Finally, for trigger types 1, 2, and 8, there was no significant difference in efficiency before and after the breaks.

Accuracy in Problem Solving

Results showed that trigger types 2 and 8 had significant effects on average accuracy before and after the breaks (Figure 3.5 (d)). Trigger type 2 was initiated upon detection of a local increase in accuracy, indicating that a student received a break based on this trigger while improving performance. The results of the t-test showed that average accuracy decreased after trigger type 2 was initiated. While the causes of this drop were not certain, we speculated that these breaks may have distracted some students in the short-term as they received them when they were in the "flow" of improving.

In the refocus condition, trigger type 8 was initiated specifically after a local performance drop was detected. Our analysis showed that students significantly improved their accuracy from before to after the breaks triggered by type 8. This improvement in accuracy following these breaks further suggests the restorative effects non-task breaks may have on performance during learning when triggered effectively. For trigger types 1, 5, and 7, there was no significant difference in accuracy before and after the breaks.

3.5.4 Additional Observations

In addition to the statistical analyses on student learning gains and perfomance in problem solving, we also made several observations and formed a preliminary understanding of students' experience of interacting with our tutoring system. Overall, we observed that the students were very engaged with the robot. They glanced periodically toward the robot and ocassionally touched the robot during the sessions. We also observed students enjoying interacting with the robot by expressing smiles and laughing. Additionally, most students followed the robot's instructions during breaks to stretch their bodies and participated in the relaxation activity.

Students rated their experience with the robot tutoring system positively on 5-point scales. There were no significant differences on these ratings between the study groups. In particular, students in the fixed ($M = 4.83$, $SD = 0.39$), reward ($M = 4.50$, $SD = 0.94$), and refocus ($M = 4.42$, $SD = 0.79$) groups felt refreshed after the provided breaks, $F(2, 35) = 1.028$, $p = .368$. Students also wanted to have a similar robot tutor to help with their math homework (fixed: $M = 4.42$, $SD = 1.24$; reward: $M = 4.50$, $SD = 1.02$; refocus: $M = 4.75$, $SD = 0.62$), $F(2, 35) = .368$, $p = .695$.

3.6 Discussion

Contributing to the increasing evidence showing the benefits of personalization in human-robot tutoring (e.g., [142, 180]), results of this work demonstrate the positive impact personalized break timing has on learning outcomes. While children in all conditions seemed to enjoy the breaks, only those in the personalized (reward and refocus) conditions showed significant learning gains (Figure 3.5 (a)). Moreover, the children with breaks on a personalized schedule outperformed those with breaks on a fixed schedule in terms of learning gains (Figure 3.5 (b)). These results show the importance of break timing during a learning interaction. Although we did not observe significant learning differences emerge as a result of employing different personalized strategies, our implementation of the reward and refocus strategies provide insight into how these strategies might be realized. Additional work is needed to explore alternative personalized strategies, such as a combination of the reward and refocus strategies, as well as other plausible implementation.

Our analysis also revealed that certain break triggers led to immediate changes in efficiency and accuracy during the tutoring interaction, providing design implications for robot tutoring systems. Specifically, breaks triggered based on negative performance changes led to desired immediate effects during learning, showing that performance-based metrics are useful features for providing breaks for cognitive rest. For example, after taking a break initiated by trigger type 5 (efficiency drop possibly signifying a negative affective state, such as disengagement), students improved their efficiency in problem solving, indicating a potential restorative effect following the break. Similarly, providing a break after trigger type 7 (timing drop, potentially due to guessing) prompted students to spend more time on problems, suggesting the break's potential to refocus the students on the learning task. Finally, breaks provided after trigger type 8 (drop in accuracy, possibly signifying frustration or confusion) led to an increase in accuracy following the break, again showing the potential of these breaks to refocus young learners. Together, these findings showed that the refocus strategy providing "positive time-out" had a positive impact on immediate learning performance. However, these personalized triggers must be carefully designed, as not all of them led to positive performance changes. Initiating trigger type 2 to provide a break when students were showing improved accuracy caused accuracy to drop after the break. Interestingly, students receiving breaks as success-based rewards still benefitted over the whole session as evidenced by their improved test scores. More research is necessary to obtain a more comprehensive understanding of the broader effects of this type of trigger.

Specifically looking at the immediate changes in performance for the accuracy-based triggers (trigger types 2 and 8), we see that the accuracy after trigger type 2 goes down and the accuracy after trigger type 8 goes up, which appears to be in line with the phenomenon of "regression towards the mean". Typically, individual student performance between problems is not independent and identically distributed, as performance on a given question may affect performance on subsequent exercises. In addition, the triggers are purposely designed to occur after "extreme" events (for example, a significant drop in accuracy) relative to the individual's baseline performance. The triggers are not designed in relation to overall average performance across individuals or across experimental groups. Furthermore, particularly for the refocus condition, we designed the break triggers to approximate events that affect student performance, such as a student becoming disengaged or frustrated. From observing the students, we felt that the triggers for the refocus group were good indicators of disengagement. This indicates that when breaks were triggered for students in this group, their performance had not randomly dropped, but instead dropped due to potential disengagement, meaning that their performance is not a randomly sampled event.

Personalization methods within educational scenarios typically focus on either what type of behavior should be utilized or when to utilize a certain type of behavior. Other work has looked at what behaviors can maintain or improve engagement during a tutoring interaction, such as the use of socially supportive utterances [37]. Rather than focus on *what* behaviors can be used to sustain engagement, we focused specifically on the *when* of providing engaging break activities to sustain attention over time, and showed that the timing of these breaks can have an impact on learning during tutoring. Another related body of work has investigated timing mechanisms for repairing engagement when attention drops during an interaction with a robot [216]. Szafir and Mutlu found that adults improved their recall of information after a story-telling task with a robot when the robot became louder and used arm gestures contingent upon drops in user attention detected by an EEG device [216]. Our results are consistent with their findings and further validates the importance of personalized timing strategies for maintaining attention within educational interactions with robots in an authentic tutoring interaction for children.

Furthermore, we designed our personalized timing strategies based on current practices derived from the educational literature. This process of designing interaction strategies based on relevant literature and prior work is one commonly used in HRI studies, largely due to the difficulty of employing strictly data-driven strategies, especially in subfields involving unique populations, such as children in a classroom environment. We derived our two personalization strategies for when to provide a break based on current educational practices that were readily applicable to the concept of providing breaks based on performance to children in a learning interaction.

We also contextualized our investigation of break timing strategies in an authentic math tutoring interaction with students learning a math concept taught in public schools. This is an important aspect of our user study, as it allows us to extrapolate design recommendations for future robot-child tutoring interactions that are experimentally validated. We were also deliberate about investigating the effectiveness of our strategies through the use of an autonomous robot tutoring system. This allows us to claim that our findings can be readily utilized in real-world educational interactions without requiring substantial experimenter intervention. We detected performance jumps and drops through features of timing and accuracy that can be robustly detected with little error using a tablet device. Further exploration should focus on more reliable detection methods for learning-centric affective states (such as boredom and confusion) in order to understand how to effectively manage a larger range of emotional and affective states during learning. The study described in this chapter as well as the subsequent chapters follow this general setup involving authentic math tutoring scenarios and autonomous tutoring interactions in order to generate feasible design guidelines that have real-world validity and can be readily deployed in robot tutoring scenarios in research environments, classrooms, or homes.

As is common with user studies in HRI, our study was conducted with a small population of children. Our study investigating personalized break timing strategies was rigorously controlled, but involved only a single tutoring session for the child and the robot. As our findings are meant to provide actionable recommendations for designing effective tutoring interactions, we should consider how these findings generalize to longer-term interactions. Robots deployed in classrooms and homes to tutor students are likely to engage with a student in multiple sessions over extended durations. In order for their full potential to sustain engagement over time to be realized, additional research should explore how our personalized strategies can be extended to handle engagement dynamics over a longer period. We do explore longer-term tutoring interactions over multiple sessions later on in this dissertation, in Chapters 5 and 6.

3.7 Summary

Maintaining attention is an important component of effective robot tutoring interactions, especially for younger students. Leveraging the idea that non-task breaks can provide cognitive rest to students during learning, we investigated whether personalizing the timing of these breaks could benefit student performance and improve learning outcomes. Our study found that providing breaks to children using personalized strategies that respond to real-time student performance changes can improve learning gains over the course of a cognitively taxing tutoring interaction. Additionally, we looked at the more immediate effects of the various types of break triggers by measuring how both accuracy and timing change from before the break to after the break. We found that break triggers based on performance drops (from the refocus condition) led to improved accuracy or efficiency directly following the break.

These results have positive implications for creating effective, personalized tutoring interactions. Though we did not find significant differences between the two personalized strategies (reward and refocus) on our measure of learning gains before and after the entire interaction, it was students who experienced the refocus strategy that significantly improved their learning gains and demonstrated restored efficiency and accuracy during the course of the interaction. Therefore, in the design of effective tutoring interactions for children, we recommend break timing personalized to performance drops as a useful tutoring interaction design mechanism that bolsters the efficacy of robot-child tutoring.

These design recommendations can be put into practice easily by researchers and by anyone looking to build effective tutoring agents for children. Personalized break timing mechanisms are one very specific aspect of a tutoring interaction that robots can employ to sustain engagement over the course of the interaction, ultimately positively impacting learning outcomes. In the next chapter, we start to investigate another set of supportive behaviors robots can use during learning, namely interactive support for students as they utilize a metacognitive strategy, which is challenging for students to successfully use. We look at an interaction in which students utilize a particular metacognitive strategy, called thinking aloud, and explore whether social robot tutors can effectively support this type of complex strategy use.

Chapter 4

Robots that Support Metacognitive Strategy Use: Thinking Aloud*

In order to be truly effective learners, students must not only learn specific subjects such as math and reading, but also learn how to understand and monitor the way they learn. These strategies are called metacognitive strategies, which are designed for students to learn to regulate their own learning processes, allowing them to be more effective overall learners and problem-solvers [78]. While some students are strong, self-regulated learners, many struggle with employing these types of high-level strategies in addition to learning the concepts presented during a learning interaction. Consequently, in the design of effective robot tutors for children, another important aspect of long-term learning involves not just adapting to a student over time, but giving the students themselves the metacognitive tools to improve their learning skills. These skills require close support to be utilized effectively. Social robot tutors have been effective in promoting learning in a variety of different subject domains, but providing support for metacognitive strategy use is an area that needs further

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exploration. Considering their social presence and tutoring efficacy, students may have an easier time employing some of these metacognitive strategies when also receiving support from a robot tutor.

In this chapter, we explore whether we can leverage the social presence of robot tutors to provide support to students employing a particular metacognitive strategy, called thinking aloud. Thinking aloud, while requiring extra mental effort, is a metacognitive technique that helps students navigate through complex problem-solving tasks. Social robots, bearing embodied immediacy that fosters engaging and compliant interactions, are a unique platform to deliver problem-solving support such as thinking aloud to young learners. We investigate the effects of a robot platform and the think-aloud strategy on learning outcomes in the context of a one-on-one tutoring interaction. Results from a 2x2 between-subjects study ($n = 52$) indicate that *both* the robot platform and use of the think-aloud strategy promoted learning gains for children. In particular, the robot platform effectively enhanced immediate learning gains, measured right after the tutoring session, while the think-aloud strategy improved persistent gains as measured approximately one week after the interaction. Moreover, our results show that a social robot strengthened students' engagement and compliance with the think-aloud support while they performed cognitively demanding tasks. This highlights the idea that the social presence a robot tutor brings to a social interaction can impact the way in which students actually interact with it during learning. The work in this chapter indicates that robots can support metacognitive strategy use to effectively enhance learning and contributes to the growing body of research demonstrating the value of social robots in novel educational settings.

4.1 Introduction

Robot tutors have been successfully used to teach a variety of traditional subjects, such as math, reading, and language learning, as well as physical learning tasks, such as handwriting or physical exercises [75, 86, 100, 116, 158, 180]. Despite the demonstrated potential of tutoring robots, little work has explored how social robot tutors may support metacognitive strategies—which are particularly important for learning independence and efficiency—in

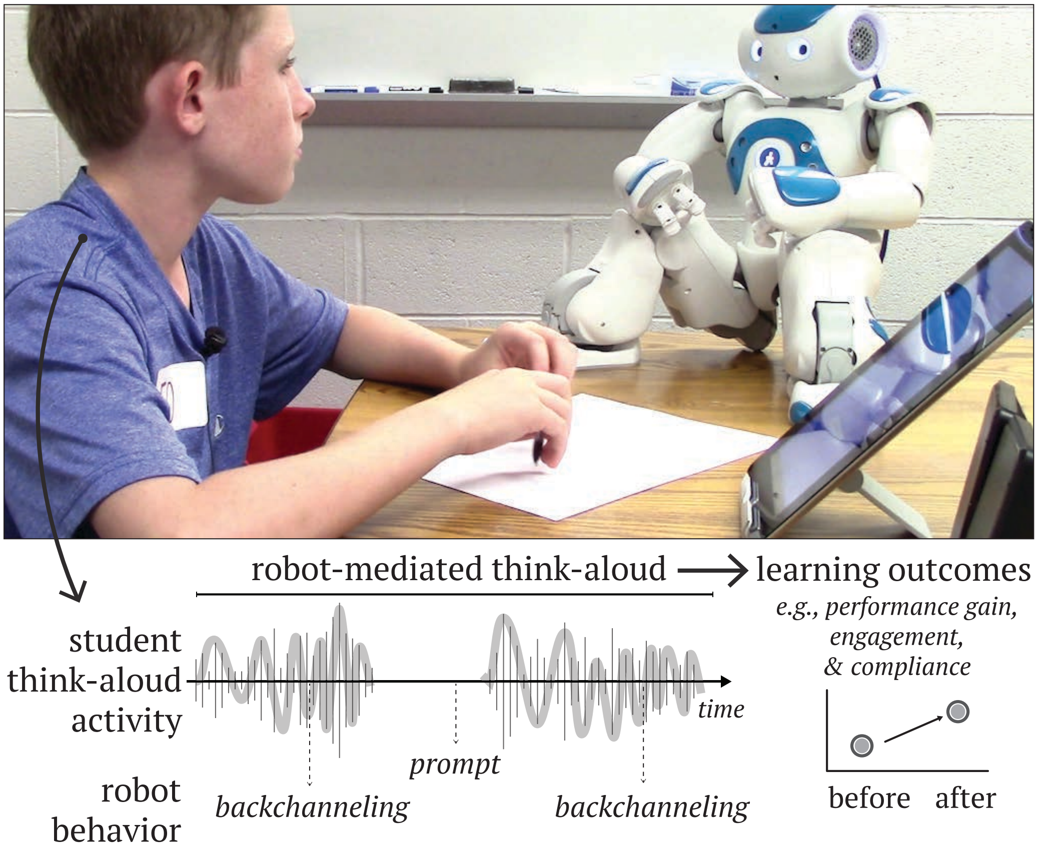

Figure 4.1: We studied how thinking aloud with a robot tutoring system can promote child learning during one-on-one tutoring interactions. We investigated the effects of both the think-aloud strategy and the robot platform on learning outcomes.

learning and solving complex problems. Metacognitive strategies are important for effective learning and academic success [78]; however, they are difficult for young children to successfully use without support [8, 172].

Thinking aloud—verbalizing one's thoughts during a cognitive task—is a metacognitve strategy that can aid students with complex reasoning tasks. Think aloud protocols are conventionally utilized as a technique for researchers to gain insight into a person's cognitive processes [72]. In tutoring interactions, thinking aloud has also been used to better understand a child's cognitive processes during educational tasks [192, 210]. More recently, teachers have been extending the use of thinking aloud as a specific problem-solving strategy for children, capitalizing on the idea that explicitly verbalizing one's thought process while trying to solve challenging problems may lead to a more deliberate and organized plan for complex reasoning [98]. However, prior research into the think-aloud method also suggests that this strategy may create additional cognitive load for the student, potentially negatively impacting performance [104, 222]. Young students are perhaps more vulnerable as they often require close support in order to successfully utilize metacognitive strategies [6].

In this chapter, we investigate whether we can leverage the social presence and embodiment of a robot to foster engagement and compliance to effectively support young students' use of the thinking aloud strategy during a cognitively complex problem-solving task (Figure 4.1). We contextualized our investigation in solving "word" problems, requiring students to use critical reasoning skills to decide what mathematical operations to perform to arrive at an answer. We built a robot tutoring system capable of supporting children as they think aloud and conducted a 2x2 between-subjects user study to evaluate the use of both the think-aloud strategy and the robot platform on measures of learning, engagement, and compliance. Because we anticipate students generally finding it difficult to employ a strategy like thinking aloud in addition to the cognitive load of doing complex word problems, in this study, we focus on evaluating both the effectiveness of the think aloud strategy itself on problem solving performance as well as how the use of a social robot tutor delivering the think aloud support impact student behavior in the think aloud activity.

4.2 Background

In this section, we present relevant work on the use of the thinking aloud strategy and its relationship to learning in various educational settings. We also highlight some work presented in Chapter 2 that explores the role of metacognitive strategies in tutoring.

4.2.1 Thinking Aloud

Thinking aloud refers to verbalizing one's thoughts out loud while completing a task. Think aloud protocols were originally developed as a tool for researchers to understand a subject's cognitive processes while engaged in a cognitive activity [72, 223]. In the educational domain, the think-aloud method has been used to gain understanding of how children of different ability levels cognitively solve math problems [159, 192]. The think-aloud method has also been used to elicit reflection in a concept learning task with adults to assess their metacognitive skill use [24].

There are many online resources[†,‡] to support teachers' exploration of metacognitive strategy use to help their students learn. Teachers have recently begun to explore an innovative use of thinking aloud as an explicit problem-solving strategy that may improve performance, in which students' verbalizations potentially lead to more carefully planned problem-solving steps [98]. Older adults demonstrated significant performance improvements on an abstract reasoning task while thinking aloud [81]. Thinking aloud also positively impacted performance for children who engaged in the strategy as they completed verbal and spatial analogies [210]. Furthermore, students who explained their steps while solving geometry problems demonstrated greater understanding of the material as compared to those who did not [6].

Although thinking aloud appears to be a promising metacognitive strategy to explore, prior work involving thinking aloud indicates that use of the strategy may become difficult when the task at hand is demanding [189]. The additional cognitive load for the user already engaged in a problem-solving task may slow down the user or negatively impact performance [104]. During an information search task, adults who concurrently engaged in a think-aloud task demonstrated lower task performance than those who did not think aloud [222]. Younger students might be particularly susceptible to this negative impact during an already challenging problem-solving task. In this chapter, we seek to explore how a social robot can provide close support to students to utilize the potential of the think-aloud strategy in solving complex problems effectively.

4.2.2 Metacognitive Strategies In Tutoring

Though metacognitive strategies are critical for student success, the idea of robots tutoring metacognitive strategies is underexplored. Some work has been done involving robots and fostering self-regulated learning (SRL) skills, which typically involves utilizing metacognitive strategies during learning [107,108]. Jones et al. have demonstrated the value of using open-

†http://inclusiveschools.org/metacognitive-strategies

‡https://www.teachervision.com/think-aloud-strategy

learner models and scaffolding to specifically encourage students to build SRL skills, such as self-monitoring, goal-setting, and help-seeking, while completing an educational task on geography [107, 108]. After investigating the effectiveness of this robot system on student behavior over several weeks, students who interacted with the adaptive scaffolding robot tutor built more SRL skills than those who interacted with a robot tutor that did not use scaffolding or an open-learner model [108]. While promising, their research focuses on several SRL behaviors at once and also focuses on the value of the open-learner modeling to bolster a student's SRL skills, rather than the role of a robot in particular. We chose to build on this type of research and deepen our investigation of how robots can support metacognitive strategy use by designing a system in which a robot tutor supports the use of thinking aloud to aid in complex problem-solving. We are the first to investigate the effects of robot support for students thinking aloud, and in this chapter, we focus on understanding whether thinking aloud benefits students with multi-step problem-solving as well as whether having the robot providing the think-aloud support impacts performance.

Aside from robot tutoring specifically, other intelligent tutoring systems have looked at student use of metacognitive strategies during tutoring [6, 8, 190]. As detailed in Chapter 2, several automated tutoring systems have looked at how to automatically assess metacognitive strategy use [9]. The most prominent work in this area done by Roll et al. focuses on one specific metacognitive strategy, which is a student's ability to seek help effectively within a tutoring environment. Their work indicates that automatic feedback provided to students based on their deviations from a computational model of help-seeking can allow students to use the system more effectively. We consider this similar problem of identifying unproductive help-seeking behavior in robot tutoring settings in Chapter 5, building off this related work from the field of ITS. In this chapter, we instead focus on robots explicitly supporting student use of the think-aloud strategy, a specific metacognitive strategy used to aid children in organizing their thinking process when solving complex problems.

4.3 Thinking Aloud with a Robot Tutoring System

In this section, we provide a detailed description of the design of an autonomous robot tutoring system capable of supporting students in thinking aloud during a learning interaction. We also present the strategies employed by the interactive system to actively encourage and respond to think-aloud behavior during tutoring.

4.3.1 System Overview

Our robot tutoring system consisted of a Nao robot as a tutoring agent and several key software components including the content manager, the voice activity monitor, and the behavior planner (Figure 4.2). The system and each of these components were implemented as part of a ROS architecture [175]. The content manager is responsible for starting the session with a short interactive lesson activity followed by up to 12 practice questions. This component manages the content of the interaction by leveling up the difficulty of the questions after the student completes four questions of a given difficulty level. The voice activity monitor uses *openSMILE*, an open source audio feature extraction tool [74], to automatically detect voice activity, and implements a speaking binary node that outputs a stream of zeros and ones to represent binary detection of a student's voice during the tutoring session. Without advanced natural language understanding, the behavior planner uses the continuous stream of speaking binary to decide when to provide certain behaviors that support the child's think-aloud activity.

4.3.2 Design of Think Aloud Support

Traditional use of think-aloud protocols indicates that subjects need to be instructed, reminded, and prompted to engage in the thinking aloud exercise [223]. To support children using a think-aloud strategy during a tutoring interaction, we included the following robot behaviors in our tutoring system. The implementation of these behaviors were informed by a pilot exploration study involving seven students thinking aloud while problem solving.

Remind— As students are not typically familiar with the think-aloud strategy, the system provides a reminder to think aloud each time a new exercise in the problem-solving

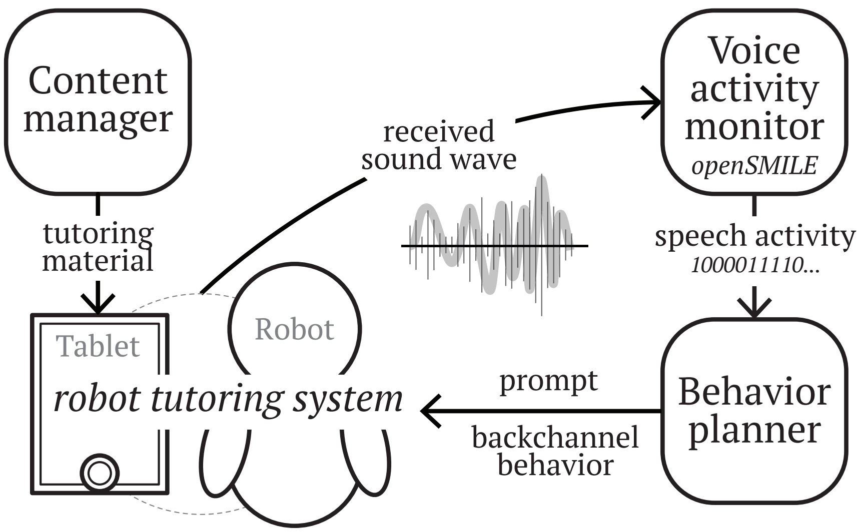

Figure 4.2: System architecture of our robot tutoring system, capable of supporting students thinking aloud during problem-solving.

task is displayed. An example reminder given by the robot is "When you are doing the question, remember to say everything out loud."

Prompt— We noticed from the exploration study that students periodically forget to think aloud when concentrating on the math problems, indicating that prompting students to continue talking out loud is necessary during a challenging problem-solving task. We observed that students would talk continuously for small periods of time lasting 5.63 seconds on average (SD = 2.22). However, they also paused frequently as they talked out loud while doing problems, leaving gaps between speech of 4.25 seconds on average (SD = 2.85). Based on these observations, we designed our robot's prompting behavior to trigger after approximately 6 seconds of detected silence, according to a dynamic sampling from a normal distribution with M = 6.00 and SD = 2.00, in order to avoid frequently interrupting students pausing to think. The robot would give prompts such as "Keep talking out loud!" or "Don't forget to think aloud!".

Reflect— When students make an incorrect attempt, the system will instruct them to reflect on why their answer was wrong and to think out loud while doing this. For example, the robot would say "Reflect on why you might have gotten the problem wrong. Make sure to think aloud as you do this."

In addition to the above supporting behaviors of the think-aloud exercise, we designed a basic backchanneling behavior conveying that the tutoring system can hear whether the child is talking. The tutoring system actively tracked the child's voice activity using *openSMILE* and constrained voice activity detection to either "talking" or "not talking." Our backchanneling behaviors involved simple nodding motions that occurred regularly during continuous speech. In particular, the robot demonstrated backchanneling after detecting approximately 2.5 seconds of talking according to a dynamic sampling from a normal distribution with $M = 2.50$ and $SD = 1.00$. This design choice is to show nods approximately twice during an average length utterance.

4.3.3 Mechanisms of Tutoring Application

In addition to the above behaviors that support the think-aloud protocol, our tutoring system included a tablet application that provided several basic mechanisms to dictate the flow of a tutoring interaction. The tablet application displayed all the necessary information on its screen and was used as an input device to enter answers during the tutoring task. At the start of each tutoring session, students completed a short, interactive lesson on a strategy for solving certain math problems (see strategy steps in Table 4.1). After the lesson, the tablet displayed questions one at a time for the student to answer. Feedback about correct and incorrect answers was displayed on the tablet screen after each answer attempt. After two incorrect attempts on a given problem, students would see feedback on the tablet while the tutoring agent employed the strategy taught at the beginning of the interaction to provide an explanation of the correct answer. These mechanisms applied to all versions of the tutoring system regardless of the various experimental conditions described in Section 4.4.2. Aside from the basic tutoring mechanisms, the robot, serving as a tutoring agent, displayed simple interactive behaviors, including looking towards the student when talking and towards the tablet when the student was working on a problem, as well as extending its arm towards the tablet while instructing the student that the next problem would appear on the tablet screen.

Table 4.1: An example of a practice math problem given to the students during the tutoring session. The left column contains the steps for solving word problems presented during the initial lesson activity. Also shown are examples of participants' think-aloud utterances that align with the steps.

Steps for Solving Word Problems	Example
#1. Read the problem.	Samantha wants to put solar panels on the roof of her house. Her roof is a flat rectangle that is 8 feet long and 10 feet wide. If each solar panel is 4 square feet, how many panels will she needto cover her roof?
#2. Figure out what information the problem gives you.	"*her roof is 8 feet long and 10 feet wide and her roof is a flat rectangle... each solar panel is 4 square feet*" (P10)
#3. Ask yourself what the problem wants you to find and what strategies you can use.	"*So we have to find out how big her roof is...if each solar panel is four square feet so we have to divide*" (P13)
#4. Make a plan for what to do to find the answer.	"*So the roof is 80 ft...if each solar panel is four square feet, we have to divide eighty by four...twenty*" (P13)

4.4 Methods

In this section, we describe a user study exploring the effects of a robot tutoring system that supports thinking aloud, as described in Section 4.3, on student learning outcomes.

4.4.1 Evaluation Context

Our user study involved a math-based tutoring interaction in which children learned a multi-step problem-solving approach for solving *word problems*, were guided to work out one example problem step-by-step, and then completed practice exercises. Word problems refer to math problems that require students to read the problem and apply some critical reasoning skills to determine how relevant mathematical concepts could be applied to the problem at hand (Table 4.1). Children typically struggle with this type of problem-solving [85]. In particular, as the number of steps required to complete each problem increases, students often feel confused and simply combine numbers mentioned in the problem to guess an answer.

We designed a total of 12 multi-step word problems on area and perimeter, which are concepts that students have learned in school but have not frequently encountered within the context of word problems. To ensure the appropriateness of the concepts and difficulty of the problems used in the study, we validated the problems with a local public school teacher who has years of experience teaching children in our targeted age range and grade level.

4.4.2 Experimental Design

We designed a 2x2 between-subjects study involving two independent variables that each contain two levels: the *platform* through which tutoring support is delivered (robot vs. no robot), and the use of the thinking aloud *strategy* during problem solving (think-aloud vs. no think-aloud). Students received the same educational content regardless of experimental condition. Below are the four conditions.

Robot&ThinkAloud— In this condition, we implemented the tutoring system as detailed in Section 4.3. This condition includes using a robot as the platform to provide tutoring intervention. Students in this condition were also explicitly instructed by the robot to think aloud and received reminders and prompts to do so throughout the tutoring interaction.

Robot-Only— In this condition, students interacted with a robot tutoring agent throughout the interaction; however, there were no think-aloud instructions, prompts, or reminders for them during the session. The robot still served as the tutoring agent and displayed the tutoring support mechanisms detailed in Section 4.3.3.

ThinkAloud-Only— Students in this condition received their tutoring support without the presence of the robot. Students were provided with verbal instructions, prompts, and reminders to think aloud from the tablet. To signal "backchanneling" behavior conveying listening awareness, we implemented a dynamic circle that varies its size depending on received voice activity.

Baseline— Students completed their tutoring session without the presence of the robot as well as without the use of the think-aloud strategy. This condition simulates the scenario in which students would use a typical tutoring application on a tablet.

4.4.3 Experimental Procedure

Prior to participation, parental and child consent forms were collected for each student. Children were informed that they were allowed to stop the experiment at any point without any repercussions. An experimenter escorted children from their classroom one at a time to participate in the study for approximately one hour. Prior to interacting with the tutoring system, students completed a pretest consisting of six word problems to assess prior knowledge. They were then randomly assigned to one of the four experimental conditions and interacted with the tutoring system for approximately 30 minutes regardless of experimental condition.

Students sat at a table facing the tutoring system that included a tablet and speakers in all conditions, and a robot in the *Robot* conditions (Figure 4.1). Each child participated in a completely autonomous interaction with the tutoring system, where no input from experimenter was required during the tutoring session. After the interaction, children completed a posttest assessment to measure their knowledge of the concepts learned. After the posttest, students then completed a short questionnaire about their interaction experience with the tutoring system and were given a pencil and a sticker for participating in the study. Approximately one week after the interaction, students also completed a follow-up posttest assessment to measure sustained performance after several days. The pretest, posttest, and follow-up assessments were identical and consisted of the same six questions that were each a word problem involving the concepts of area or perimeter.

4.4.4 Measures

To evaluate the benefits of the use of the think-aloud strategy as well as the platform through which the tutoring support was delivered on both learning outcomes and student behavior during the think-aloud activity, we employed several objective measures involving (1) learning gains, (2) engagement, and (3) compliance. To measure learning gains, we used normalized learning gain (nlg) between two test scores, which is defined as follows for an individual student i:

$$nlg(i) = \begin{cases} \dfrac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{1 - score_{\text{pre}}(i)} & \text{if } score_{\text{post}} \geq score_{\text{pre}} \\ \\ \dfrac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{score_{\text{pre}}(i)} & \text{if } score_{\text{post}} < score_{\text{pre}} \end{cases} \tag{4.1}$$

Measuring nlg, which ranges from -1.0 to 1.0 in this case, captures normalized change between individual test scores, and provided us with a single metric of improvement for each individual that accounts for varying prior knowledge levels by measuring improvement relative to each student's pretest accuracy. For this study, we chose to use the variant of of nlg that measures loss out of a student's total potential loss, as we did not know if more students would demonstrate losses due to the potential cognitive burden of thinking aloud. The measure of *score* itself is not a normalized value, but rather a measure of accuracy for an individual student on a given test (pretest, posttest, or follow-up) calculated by dividing the number of questions answered correctly by the total number of questions on the test. We analyzed nlg from pretest to posttest as well as nlg from pretest to follow-up to understand our system's effects on immediate learning outcomes as well as those that remain several days after the tutoring session.

In addition to evaluating learning outcomes, we sought to understand how the platform through which the tutoring support (e.g., thinking aloud) is delivered can impact children's engagement in and compliance with the intended support. To quantify children's engagement in the thinking aloud exercise, we derived two measures—the percentage of time students talked during the tutoring session and the number of prompts needed to keep the students thinking aloud. The percentage of time talking, extracted automatically from the logged openSMILE voice activity data, was calculated by dividing the amount of time that talking was detected over the total time students were given the opportunity to be talking out loud during the problem-solving task. This measure excludes times when the tutoring agent was talking, prompting, or giving any instructions intermittently throughout the session. We interpret a higher percentage of talking during the tutoring sessions as higher engagement in the tutoring support, as it signifies active utilization of the think-aloud strategy over the duration of the tutoring session. On the other hand, fewer prompts needed to have the students continue talking indicates higher engagement.

To assess students' compliance with the tutoring support, we calculated the number of prompts the students ignored during the session. We define an ignored prompt as a prompt that goes unanswered due to a lack of voice activity detection and subsequently triggers an additional prompt due to the prolonged silence. Fewer ignored prompts indicates higher compliance with the support.

4.4.5 Participants

We recruited 53 participants from local middle schools to participate in this study. We excluded one participant from this data analysis due to a perfect pretest score, resulting in 13 participants in each experimental group. The included 52 participants were comprised of 14 females and 38 males that were gender-balanced across groups. The majority of the students in this study were in sixth grade, with the average age being 11.21 years old ($SD = .89$). Pretest scores for the four groups were: Robot&ThinkAloud ($M = .36$, $SD = .33$); Robot-Only ($M = .31$, $SD = .23$); ThinkAloud-Only ($M = .15$, $SD = .21$); Baseline ($M = .14$, $SD = .24$). As students were randomly placed into each of the four groups, a one-way ANOVA showed no statistical differences between the four groups, $F(3, 48) = 2.362$, $p = .083$, regarding the pretest.

4.5 Results

In this section, we first our present findings on how students progressed over the course of the tutoring session, which informs our further analysis. We then present results characterizing the learning outcomes of students across our experimental groups (Figures 4.3 and 4.4) as well as differences in engagement and compliance behaviors between our two *ThinkAloud* conditions (Figure 4.3). We used analysis of variance (ANOVA) tests when comparing all groups and t-tests when directly comparing the two *ThinkAloud* conditions. We used non-parametric statistical tests when appropriate and an α level of .05 for significance in our analysis.

4.5.1 Characterization of Learning Progress

Students completed up to 12 practice problems during their tutoring session, limited by an overall time limit to ensure students spent approximately the same amount of time with the system in all conditions. Students in the four experimental groups progressed through the exercises comparably, with no significant differences across groups in the number of the problems they were able to complete during their session (Robot&ThinkAloud: $M = 10.85, SD = 2.34$; Robot-Only: $M = 10.54, SD = 2.07$; ThinkAloud-Only: $M = 9.62, SD = 2.67$; Baseline: $M = 10.23, SD = 2.20$).

To explore the broader benefits of the tutoring system, we administered follow-up tests to examine students' persistent performance after several days following the session. In this exploration, we observed that many students improved their problem-solving performance on the follow-up test rather than on the posttest (Figure 4.4).

4.5.2 Learning Gains

To evaluate the effect of our two independent variables—platform and strategy—on learning outcomes, we first compared normalized learning gain, nlg, from pretest to posttest using a two-way ANOVA test (Robot&ThinkAloud: $M = .37, SD = .49$; Robot-Only: $M = .39, SD = .40$; ThinkAloud-Only: $M = .19, SD = .50$; Baseline: $M = -.02, SD = .31$). This analysis revealed a significant main effect of platform (robot or no robot) on nlg from pretest to posttest, $F(1, 48) = 6.785$, $p = .012$, $\eta^2 = .120$. Students who interacted with the robot improved from pretest to posttest (nlg: $M = .38$, $SD = .41$) significantly more than those who did not interact with the robot platform (nlg: $M = .08$, $SD = .42$), suggesting the benefit of using a robot as a platform to deliver tutoring support. There was no significant main effect of strategy (think-aloud or no think-aloud) on nlg from pretest to posttest ($F(1, 48) = .716$, $p = .402$, $\eta^2 = .013$), nor was there a significant interaction effect, $F(1, 48) = 1.139$, $p = .291$, $\eta^2 = .020$.

As informed by our observations of students' improvement on the follow-up test, we compared nlg from pretest to follow-up (Figure 4.3) using a two-way ANOVA to compare the learning gains from before the tutoring session to approximately one week after the

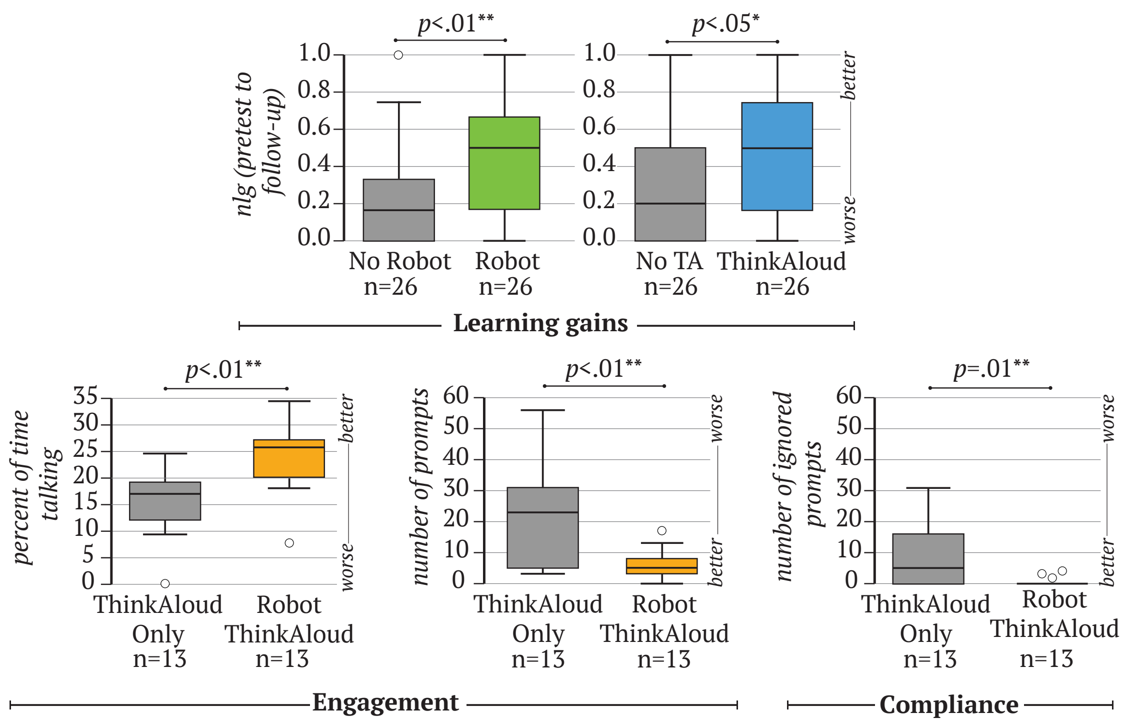

Figure 4.3: Our results show the benefits of thinking aloud with an interactive robot system. *Learning gains*: Both the robot and the think-aloud strategy led to improved learning from pretest to follow-up. *Engagement*: students talked significantly more and required fewer prompts to continue talking when thinking aloud with the robot. Higher engagement corresponds to more talking and fewer prompts. *Compliance*: Students ignored fewer prompts to talk out loud when thinking aloud with the robot. For all boxplots, the line inside the box represents the median and the extents of the box are the first and third quartiles.

session (Robot&ThinkAloud: $M = .52, SD = .39$; Robot-Only: $M = .44, SD = .32$; ThinkAloud-Only: $M = .39, SD = .36$; Baseline: $M = .09, SD = .11$). We found a significant main effect of platform on nlg from pretest to follow-up ($F(1, 48) = 7.350$, $p = .009$, $\eta^2 = .119$), which shows that students who interacted with the robot platform ($M = .48$, $SD = .35$) improved significantly more than those who did not ($M = .24$, $SD = .30$). Additionally, we also found a significant main effect of strategy on nlg from pretest to follow-up ($F(1, 48) = 4.743$, $p = .034$, $\eta^2 = .077$), indicating that the mean nlg was significantly higher for those who engaged in the think-aloud strategy ($M = .45$, $SD = .37$) than those who did not utilize the think-aloud strategy ($M = .27$, $SD = .29$). However, there was no significant interaction effect of platform and strategy on nlg from pretest to follow-up, $F(1, 48) = 1.549$, $p = .219$, $\eta^2 = .025$.

We further investigated each experimental group separately to understand which groups demonstrated *immediate* learning gains from pretest to posttest and *persistent* learning gains from posttest to follow-up. We performed Wilcoxon Signed Ranks tests to evaluate the differences between consecutive pairs of test scores (see Figure 4.4 for a visual representation of these results). Students in the robot conditions, including both the Robot&ThinkAloud group and the Robot-Only group, significantly improved their test scores from pretest to posttest. In contrast, students in the ThinkAloud-Only group and the baseline group showed no significant difference between pretest and posttest scores. We further analyzed the differences in performance from posttest to follow-up. In this analysis, we excluded participants who achieved a perfect score on the posttest across all groups due to no improvement being possible for these students. Our analysis revealed that students who engaged in the think-aloud activity, including both the Robot&ThinkAloud group and the ThinkAloud-Only group, showed significant improvements on their test scores between the posttest and follow-up. However, the Robot-Only group did not show additional improvements between the posttest and follow-up, nor did the baseline group.

Taken together, the observed improvements from pretest to posttest for those who interacted with the robot, as well as the improvements from posttest to follow-up for those who engaged in the think-aloud activity, indicate the potential of both the robot platform and the think-aloud strategy on learning outcomes. Moreover, the Robot&ThinkAloud group demonstrated both immediate (from pretest to posttest) and persistent (from posttest to follow-up) improvements, suggesting the promise of a robot in reinforcing metacognitive strategies, particularly thinking aloud, in an educational application.

4.5.3 Engagement

Engagement is critical to student learning and achievement [77]. Below, we report our findings on two measures of student engagement to further explore how a robot's social presence impacts engagement during a metacognitive educational task.

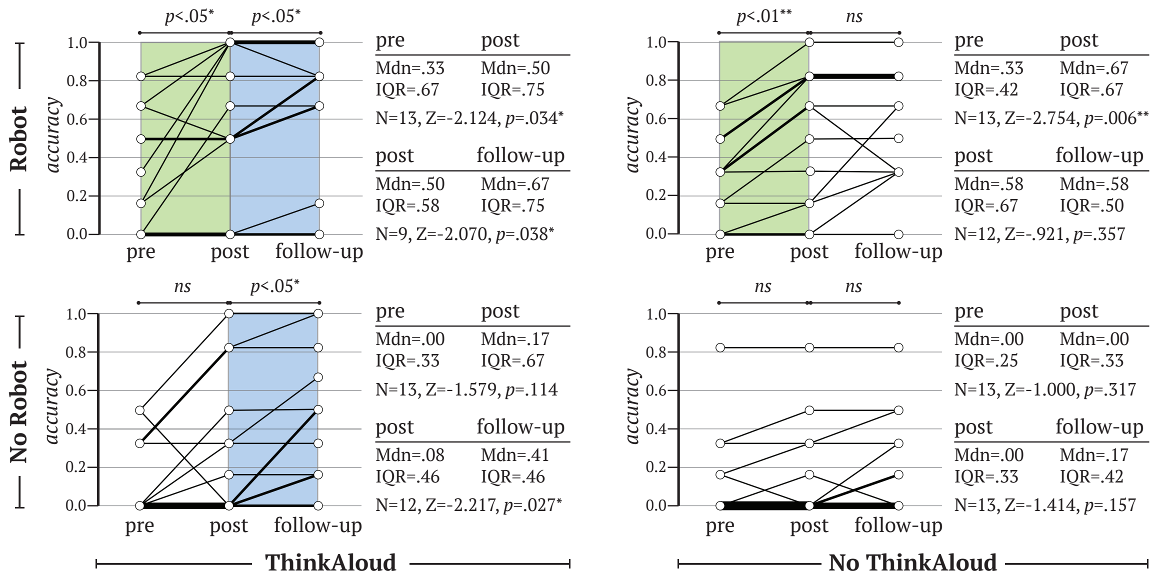

Figure 4.4: Pretest, posttest, and follow-up scores for each student, separated by experimental condition. Thicker lines indicate multiple participants with the same scores. Students that interacted with the robot improved their scores significantly between pretest and posttest (shaded in green) regardless of think-aloud strategy use. Students that engaged in the think-aloud strategy improved their scores from posttest to follow-up (shaded in blue) regardless of platform. The Robot&ThinkAloud group showed both immediate and persistent learning gains. (*) and (**) denote $p < .050$ and $p < .010$, respectively.

Percent of Time Talking

The percent of time students talked during the tutoring session is an approximate measure of their engagement in the think-aloud tutoring activity. We conducted a two-way ANOVA to measure the effects of our two independent variables on the percentage of time students talked during the tutoring interaction (Robot&ThinkAloud: $M = 23.77\%, SD = 6.68\%$; Robot-Only: $M = 2.60\%, SD = 5.47\%$; ThinkAloud-Only: $M = 15.81\%, SD = 6.70\%$; Baseline: $M = 4.31\%, SD = 6.49\%$). A significant main effect of strategy demonstrated that students in the *ThinkAloud* groups ($M = 19.79\%$, $SD = 7.71\%$) talked significantly more than those who completed the tutoring interaction without the thinking aloud activity ($M = 3.46\%$, $SD = 5.94\%$), $F(1, 48) = 85.892$, $p < .001$, $\eta^2 = .594$. This is expected as students do not typically talk out loud very frequently unless explicitly instructed to do so. This result confirms that students who participated in the think-aloud exercise actively engaged in the task and talked out loud more frequently than those who were not given think-aloud instructions or support.

While no significant main effect of platform on percent time talked was found ($F(1,48) = 3.136$, $p = .083$, $\eta^2 = .022$), the test revealed a significant interaction effect between strategy and platform on percent time talked, $F(1,48) = 7.523$, $p = .009$, $\eta^2 = .052$. This result indicates that the effect of the think-aloud strategy on how much students talk differs based on the platform. A simple effects test between the Robot&ThinkAloud group and the ThinkAloud-Only group (Figure 4.3) showed that students talked out loud significantly more when thinking aloud with the robot ($M = 23.77\%$, $SD = 6.68\%$) than when thinking aloud without the robot ($M = 15.81\%$, $SD = 6.70\%$), $p = .002$.

Prompts to Think Aloud

In both the Robot&ThinkAloud and the ThinkAloud-Only conditions, the tutoring system prompted the students to continue thinking aloud when periods of silence were detected. Here, we report the comparison of how often these prompts were triggered between the two think-aloud conditions (Figure 4.3). An independent samples t-test showed that students who interacted with the robot triggered fewer prompts to continue thinking out loud ($M = 6.08$, $SD = 4.70$) as compared to those who completed the activity without the robot ($M = 22.23$, $SD = 17.84$), $t(24) = -3.156$, $p = .004$, $d = 1.24$. This finding indicates that students needed fewer reminders to stay actively engaged in the think-aloud exercise when interacting with the robot. We speculate that the social presence and embodiment of the robot might contribute to such active engagement.

4.5.4 Compliance

Effective tutoring agents need to foster student compliance with the educational strategies they deliver during the interaction. Here we report the students' compliance with the think-aloud exercise, as measured by the number of prompts that were ignored by the students (Figure 4.3). An independent samples t-test showed that students in the Robot&ThinkAloud condition ignored significantly fewer prompts ($M = .69$, $SD = 1.37$) than students in the ThinkAloud-Only condition ($M = 9.23$, $SD = 10.97$), $t(24) = -2.784$, $p = .010$, $d = 1.09$. Students interacting with the robot tutoring agent complied with the request to continue talking more often than those completing the think-aloud exercise without the robot. Furthermore, we see that students who did the think-aloud activity with the robot were almost fully compliant, as the average number of ignored prompts across students in this group was close to zero. This high level of compliance with the robot's requests further indicates the effectiveness of the robot platform in supporting students' megacognitive strategy use that may be difficult for them.

4.6 Discussion

In this chapter, we explore the effects of two variables—the use of a metacognitive learning strategy and the platform through which the tutoring support is delivered—on student learning outcomes during a tutoring task. We found that students benefited from both interaction with the robot tutoring platform as well as from engaging in the think-aloud strategy during problem-solving. We also observed that during the think-aloud exercise, the robot fostered increased engagement and compliance, two important ingredients for achieving effective tutoring. Our findings further highlighted two phases of learning improvements, as we observed the robot's impact on immediate learning gains and the think-aloud strategy's effect on persistent gains measured a week after the tutoring session.

Our results showed that students who interacted with the robot tutoring platform outperformed those who did not, as indicated by normalized learning gain from pretest to follow-up (Figure 4.3). Moreover, students who interacted with a robot improved their performance from pretest to posttest, demonstrating immediate learning gains after a single tutoring session. We speculate that this immediate benefit may come from the embodied social presence that the tutoring robot fostered during the interaction, as empirical evidence has suggested various positive influences of the perceived social presence of robots on human-robot interactions [2, 112, 119]. Learning improvement from posttest to follow-up, however, was not observed in the Robot-Only group, yet their performance did not drop either, suggesting that the problem-solving skills they improved during the tutoring session remained when measured several days later.

The use of the think-aloud strategy did not lead to the same immediate benefits as the robot platform, as students in the ThinkAloud-Only group did not show immediate learning gains from pretest to posttest. Due to the additional mental effort needed for the think-aloud activity, some students may have experienced increased cognitive load during the tutoring exercise. The intense cognitive burden, coming from both the think-aloud activity and the problem-solving task, could have potentially drained students' attention and patience in completing the posttest assessment. However, students who completed the think-aloud activity demonstrated learning improvements from posttest to follow-up, indicating that they were able to demonstrate improved problem-solving performance after receiving a cognitive break of a few days. Though it took longer for the benefits to become observable, these learning improvements for students in the ThinkAloud groups showed that the metacognitive strategy of thinking aloud did help students' problem-solving skills.

Students in the Robot&ThinkAloud group demonstrated both immediate and persistent learning gains, indicating that robot tutoring agents are a promising platform through which to deliver metacognitive strategy support for children. One possible explanation of these observed gains is that students in the Robot&ThinkAloud condition had a social entity to direct their thinking aloud towards, as if they were engaged in a regular talking activity. For example, one student frequently referenced the robot while thinking aloud: "*then you multiply seven times seven* [looks toward robot] *equals forty-nine* [looks at robot again]*, right?*" In contrast, when there was no social entity to talk to, students might have had to deliberately carry the cognitive burden of thinking aloud.

We also observed that students in the baseline condition did not demonstrate large improvements in either of the two phases (Figure 4.4). This may be because of the cognitively taxing problem-solving interaction they completed, without any added strategy or platform that increased the engagement or novelty of the task at hand. This highlights the need to continue exploring novel technological interaction paradigms for children in tutoring settings.

Though we randomly distributed students into our experimental groups and saw no significant pretest score differences when comparing all four groups, the average pretest score for those in the *Robot* conditions was higher than for those who did not interact with the robot. It is difficult to ensure that pretest scores are equal across groups when conducting this type of real-world user study, and in this case, our experimental conditions were not perfectly balanced. This might be an additional factor that contributed to the main effect of the robot platform. Prior research has shown the importance of embodiment and social presence on learning outcomes; however, in this study, this difference in pretest scores is a limitation that should be explored further to understand to what extent the robot platform led to increased learning gains as compared to those who did not interact with the robot.

The results we observed about students engaging and complying with the think-aloud support more effectively when it was delivered by the robot are consistent with several findings showing the differences in user behavior and engagement when interacting with a physically-present robot over a screen representation or other non-embodied agents [18,112, 119,143,168,173]. Our results look at engagement with the think-aloud support specifically, but this is a novel type of engagement and compliance evaluated for children completing a challenging math task. This demonstrates the value social robots can have in challenging tutoring interactions, specifically with younger students who may not typically be as engaged with traditional classroom technologies.

Though we did not conduct a full analysis of the content of each child's speech during the think-aloud exercise, we observed variety in the quality and content of students' utterances when thinking aloud. For example, some students were clear in their ability to plan and execute their problem-solving steps. One participant quickly deduced that the problem was asking about perimeter: "*So we need to find out the perimeter, because they said we need to find out the distance he needs to walk around the building.*" Another student demonstrated organized steps to find the perimeter: "*Oh, we have to find the perimeter...so we have to multiply ten times two, which is twenty, and then thirty times two, which is sixty, then add those two together, and that would be sixty plus twenty...eighty.*" Others were less organized in their reasoning and often started talking about numbers without planning: "*Eight minus four is four, twelve minus eight...ok, it's forty four.*"

It is currently extremely difficult to automatically do speech-to-text extraction for children [118]. As this technology improves over time, it would be useful to understand whether the content or quality of the think-aloud utterances differ as a result of the platform through which the strategy was supported. Our robot tutoring system used real-time voice activity detection to interactively prompt and backchannel during tutoring; however, this voice activity detection was limited to talking and silence. To leverage the think-aloud strategy effectively, tutoring systems should work towards intelligent understanding of the students' think-aloud dialogue to provide timely interventions that can help students to prevent mistakes or flawed solution paths. There are also many factors that may contribute to differences in the quality of the think-aloud content, including prior abilities, personality traits, and academic confidence. As robot tutors become more sophisticated in their abilities to detect these attributes, building more comprehensive student models and responding to these differences should be explored. Given the current limitations and difficulty of doing this, we discuss an intuitive approach to designing robot intervention behaviors that accounts for the linkage between complex user states and observable student behaviors in Chapter 5.

The work we conducted in this chapter has several of the same properties as the study described in Chapter 3. We built a completely autonomous robot tutoring system and contextualized our investigation in an authentic math tutoring task, focusing on problem-solving skills that students actually employ frequently in school. This allows us to conclude our results have real-world validity and it is straightforward to understand how others creating autonomous tutoring interacitons may apply our design decisions in a new system. Close, responsive support from an interactive robot tutor can impact the way a child utilizes the think aloud strategy and the social presence of the social robot itself is important in fostering immediate learning gains. While these design recommendations are important, our robot tutoring system supported children using one particular metacognitive strategy—thinking aloud—in one educational domain: multi-step math word problems. To fully understand how metacognitive strategy use can benefit learning, future research in robot tutoring systems must explore the transfer of metacognitive strategy use to other educational domains as well. Finally, as metacognitive strategies are considered to be extremely complex skills for children to learn and employ successfully, our study is limited in that it considers a single tutoring session. Though our investigation included a follow-up assessment which broadened our understanding of student learning outcomes in this context, we must investigate robots supporting these strategies over longer periods of time to assess the impact on longer-term learning gains.

4.7 Summary

Metacognitive strategy use is important for students to learn to become effective long-term learners. Our work is among the first to explore the use of robot tutors as providers of support for children engaging in a metacognitive strategy. We presented empirical evidence showing the benefits of both a robot tutoring platform and use of the think-aloud strategy on student learning outcomes. Our analysis highlights two phases of learning improvements: the physically embodied robot tutor fostered immediate learning benefits, while the think-aloud strategy's positive impact on learning took longer to become observable, signifying potential longer-term benefits. We also found that students completing the think-aloud exercise engaged and complied with the support more effectively when it was delivered through the robot tutoring platform. Our work reinforces the promise of social robot tutors to support children with metacognitive strategy use in challenging learning environments.

Our user study showed that students benefitted from completing the think-aloud exercise regardless of whether they completed the initial tutoring interaction with the robot. Yet those students who did complete the same tutoring interaction with the robot showed improvements directly after the tutoring interaction. Students who completed the tutoring session with the robot and utilized the think-aloud strategy (Robot&ThinkAloud group) received the benefits of both of these factors in their learning performance. Because of these two different types of gains, our design recommendations for building effective robot tutors involves creating interactive support for students with a physically-present social robot. Especially as novel tutoring systems are designed for special populations, or for students who may be struggling, building robot behaviors that are reactive to the individual user provides a more personalized experience, which contributes to the effectiveness of the interaction.

Metacognitive strategies are useful skills to explicitly teach children. Because they are particularly difficult for children to robustly learn and employ effectively, another approach to promoting effective learning in tutoring is to design robot behavior to counter strategies that children use that are not effective. In the next chapter, rather than explicitly teach a metacognitive strategy, we explore robot tutors that can counter ineffective behaviors and attempt to shape student behaviors that may lead to more effective learning. We also describe a pipeline that is useful in designing intervention behaviors for tutoring interactions that makes use of the link between certain complex user traits and observable behavior within a tutoring setting. Specifically, we look at how measures of motivation correlate to help-seeking behavior, and start to explore whether a robot tutor that counters ineffective help-seeking behavior can affect student learning in a longer-term tutoring interaction.

Chapter 5

Robots that Shape Behavior in Tutoring: Help-seeking Strategies*

Another critical component of effective learning involves a student's motivation [70]. Internal motivation is an important factor that has been linked with academic success and often corresponds to metacognitive strategy use [60, 238]. However, these complex motivational factors vary greatly between students, making it difficult for tutoring systems to perceive these differences and behave accordingly. Because of the challenges dealing with unobservable attributes such as motivation and how difficult it is to explicitly teach students metacognitive strategies, a more practical approach for designing robot behaviors that account for these factors and enhance robot tutoring effectiveness is needed. Given the link between a student's motivation and their behavior during learning, if we enable robots to detect more observable behaviors that may be unproductive to learning, robot tutoring systems may be able to counter these behaviors and steer a student toward more productive learning. One metacognitive strategy that may be associated with internal motivation that students typically struggle with in automated tutoring environments is productive help-seeking behavior. Leveraging the effectiveness of social robots to enhance student engagement and compliance in learning interactions [18, 112, 168], robot tutors may be able

∗Part of the work in this chapter is currently in submission [179]. Portions of this chapter were originally published as: Aditi Ramachandran, Alex Litoiu, and Brian Scassellati. Shaping Productive Help-Seeking Behavior During Robot-Child Tutoring Interactions. In *Proceedings of the 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 247-254, 2016 [180].

to intelligently intervene when unproductive behavior is observed, and potentially improve behavior and learning performance if these intervention behaviors occur over a longer period of time.

In this chapter, we demonstrate that motivation in young learners corresponds to observable behaviors when interacting with a robot tutoring system, which in turn impact learning outcomes. We describe a user study involving children interacting one-on-one with a robot tutoring system over multiple sessions. Based on empirical data, we show that academic motivation stemming from one's own values or goals as assessed by the Academic Self-Regulation Questionnaire (SRQ-A) correlates to observed suboptimal help-seeking behavior during the initial tutoring session. We then show how an interactive robot that responds intelligently to these observed behaviors in subsequent tutoring sessions can positively impact both student behavior and learning outcomes over time. Our user study demonstrates the importance of productive help-seeking behavior within learning and shows that robot tutors can enhance learning by countering ineffective help-seeking behaviors exhibited by children. Taken together, these results provide empirical evidence for the link between internal motivation, observable behavior, and learning outcomes in the context of robot-child tutoring. We also identified an additional suboptimal behavioral feature within our tutoring environment and demonstrated its relationship to internal factors of motivation, suggesting further opportunities to design robot intervention to enhance learning. We provide insights on the design of robot tutoring systems aimed to deliver effective behavioral intervention during learning interactions for children.

5.1 Introduction

One aspect of a learner that varies significantly between children is a student's motivation [61, 70]. Differences in motivational goals and tendencies can notably influence students' academic performance as well as learning outcomes [70,238], indicating that a child's motivation in learning plays a large role in the type of personalized support they may require [164]. Motivation is a complex construct that involves various factors driving someone to engage in certain behaviors; for younger learners this can be measured in terms of externally and internally motivated reasons for why they do certain school-related activities [61]. Externally-driven motivation involves engaging in activities in order to receive rewards or avoid consequences that are specifically external to the person, such as money or getting in trouble with a teacher. Internally-driven motivation refers to engaging in various behaviors to achieve internal satisfaction or act in accordance with one's own goals or values, such as doing work because it's enjoyable or practicing a skill due to a belief that it is important to learn. Internal motivation includes *intrinsic* motivation, which is defined as doing something because it is inherently interesting or enjoyable and reflects a person's highly internal satisfaction in engaging in an academic task [196]. Intrinsic motivation is positively associated with self-regulation and academic success [60, 238]. Students who are intrinsically motivated are often considered to be self-regulated learners, as they typically apply strategies to monitor and evaluate their own learning processes [236, 237]. While intrinsic motivation is important for academic success, there are also other categories of motivation, such as *identified* and *introjected* motivation, that stem from an inner acceptance of the value or utility of a task, making these types of internal motivation positive sources of motivation that are also useful in fostering productive learning [196]. These internal categories of motivation have also been shown to correspond to positive coping strategies with failure experience in an academic setting [195].

Robot tutoring systems, capable of engaging in embodied interactions and maintaining situated awareness of the learning environments and users, hold the promise to deliver effective personalized learning. To fully support personalized learning, it is crucial that these systems consider students' motivation as part of their personalization approaches. However, it is challenging to decipher a person's motivation in learning, which involves hidden factors and processes that cannot be acquired intuitively and directly via computing technologies. While it is difficult to directly access the internal information of a person's motivation, human behavior often reveals information about a person's internal states, including information about attention, emotion, and motivation. Therefore, in practice, we must explore robot tutoring systems that monitor and shape students' observable, manifested behavior without direct access to their internal states. Identifying how such observable behaviors are linked to motivation in learning can help develop a holistic understanding of the learning process and can inform the design of effective robot tutoring systems. We aim to understand whether robot tutoring systems can leverage this understanding in order to provide intelligent intervention behaviors that have the potential to positively impact student learning outcomes.

In this chapter, we describe the linkage of motivation in learning, observable behavior, and learning outcomes, highlighting how motivation closely relates to behavior within a learning interaction, which in turn can be used intelligently by a robot tutoring system to intervene accordingly to strengthen learning outcomes. In a user study involving children interacting with a robot tutoring system over multiple sessions (Figure 5.1), we first show how motivation in learning as assessed by a self-reported questionnaire directly relates to observed "suboptimal" help-seeking behaviors. We further demonstrate that a robot tutoring system responding intelligently to the occurrence of these particular suboptimal behaviors can improve behavior and positively affect learning gains. Our results inform the design of robot tutoring systems aiming to deliver effective intervention that supports a broader learning process that includes the role of motivation in learning.

This work presented in this chapter makes the following contributions: We describe the unified linkage of motivation in learning, observable behavior, and learning outcomes, which can be used as a tool to design robot intervention behavior. We also empirically evaluate this tool within the context of a user study involving a robot-child tutoring scenario, demonstrating the potential for this tool to be used in building an effective tutoring system that can impact learning. We present empirical findings from the user study we conducted, showing that a robot that employed shaping strategies to counter suboptimal help-seeking behaviors (requesting too much or too little help) that relate to motivation improved the help-seeking behavior and learning gains of students over four tutoring sessions. These findings add to the broader knowledge of how motivation plays a role in robot-child tutoring interactions and informs how robots can leverage the relationship between motivation and behavior to improve behavior and enhance learning as effective tutors for children.

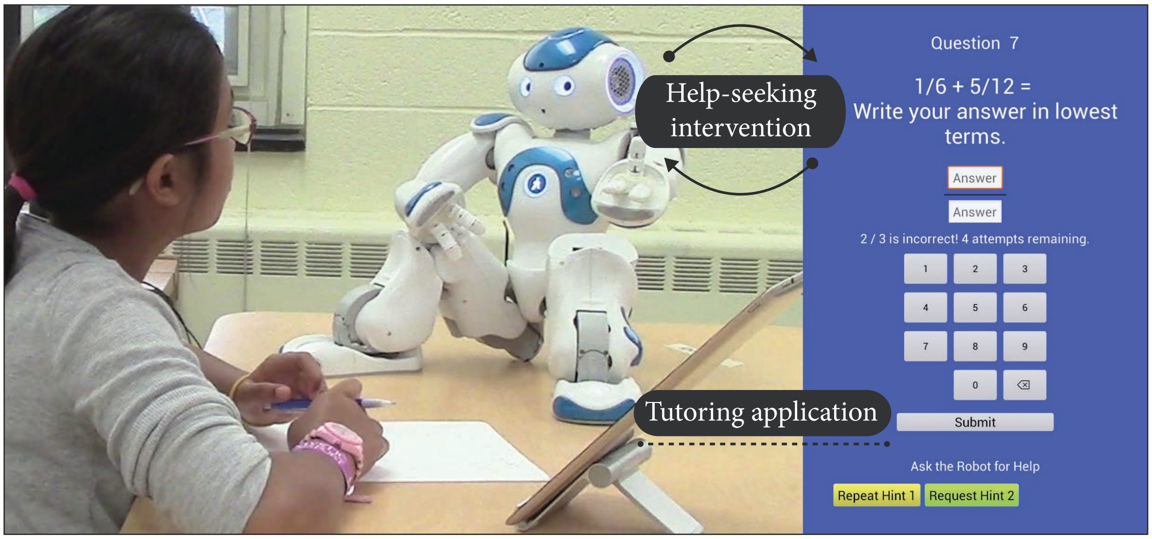

Figure 5.1: We designed an interactive robot tutoring system to provide help to children practicing math problems. Children interacted with the robot through a tutoring application on a tablet device and could ask the robot help through buttons on the tablet screen. The robot system was designed to intervene intelligently based on the help-seeking behavior of the children. The students engaged in autonomous robot tutoring interactions, in which the experimenter did not intervene at any point during the sessions.

5.2 Background

Motivation in learning is a particularly complex construct that includes both internal (e.g., to achieve personal satisfaction or to act in accordance with one's values) and external (e.g., to avoid punishment) factors that dictate why children engage in certain academic behaviors. Different motivational profiles of students can affect reactions to successes and failures and can impact a child's cognitive performance [70]. Research in educational psychology has established the positive relationship between motivation and success in learning [60, 232, 238]. In particular, intrinsic motivation contributes crucially to a child's success in an academic environment [60]. Students who were motivated by learning goals, which reflects a more internal orientation towards learning, displayed cognitive achievement, particularly during challenging tasks [71]. Moreover, measures of children's internally-oriented motivation have also been positively correlated with traditional achievement measures, such as standardized test scores and grades [89, 199]. Learning outcomes refer generally to measures of performance related to an educational task or program. These can refer to academic measures such as improvements in grades or test scores and are typically used to reliably demonstrate what a learner knows and does not know. To foster motivation in learning, prior work has explored the use of stimulating learning environments, open classrooms, and constructive feedback [60, 96, 150, 212]. These foundational efforts establish the impact of internal motivation on academic performance within the classroom and beyond.

Students who are intrinsically motivated tend to engage in self-regulated learning (SRL) by applying strategies to monitor their own learning processes and drive them forward [171, 172]. These strategies often involve employing metacognitive skills such as goal-setting, adaptive help-seeking, and persistence through difficulty [172, 236]. Prior research has explored the employment of these skills through the use of questionnaires and interviews with students and teachers and the association of them to academic achievement [172, 194, 238]. In addition to questionnaire and interview probing, more current efforts have made progress on automatically assessing user behavior through user computer traces and observation [16, 94, 237]. One prominent effort to capture SRL was by using a computer-based study environment that provided the learner with opportunities to make notes, search for information, receive help, and chat with fellow students and analyzing when and how frequently students engaged in these behaviors [230]. Other attempts to assess student use of SRL have relied on learning environments that record students thinking aloud or allow them to write down their thoughts during learning and then coding and categorizing these responses based on whether they demonstrate SRL processes [93, 205]. Another method of automatically evaluating student use of a specific SRL strategy, namely help-seeking, involved developing a model of appropriate help-seeking behavior and assessing student actions based on whether they were in line with the model [9]. This body of work has primarily focused on identifying productive behaviors and showing that using them positively impacts learning outcomes.

Identifying students who do not utilize these SRL strategies is critical, as they may require more tailored support from an interactive learning environment to be able to meet their learning goals. To this end, other work has focused on the complementary problem to identifying behavior productive to learning, which is identifying unproductive strategies that do not lead to more effective learning. This is particularly useful as the successful identification of these unproductive behaviors provides an interactive tutoring system the opportunity to monitor suboptimal behavior, meaning behaviors that do not make effective use of the tutoring system, and potentially intervene accordingly. For example, ITS systems have explored this specifically in the context of help-seeking behavior, as productive help-seeking is a critical skill positively associated with SRL [82,163,193]. The existing ITS literature has shown that the use of exploitative help-seeking behavior ("gaming the system") and help-averse behavior (sometimes called help avoidance) in students who interact with learning environments can negatively impact learning outcomes [7, 23]. We describe each of these behaviors and provide examples in the context of ITS.

Gaming the System— In the context of tutoring systems, gaming the system has been defined as "attempting to succeed in a learning environment by exploiting properties of the system rather than by learning the material and trying to use that knowledge to answer correctly" [21]. There are many examples of this behavior observed within intelligent tutoring systems. Two notable examples include inputting answers quickly and systematically and rapid hint requests [23]. Specifically related to help-seeking behavior, rapid hint requests typically involve the learner trying to acquire the answer or information about the answer without expending considerable effort thinking through each hint and the problem. In many of the intelligent tutoring systems in which gaming behavior has been detected, each problem will contain a series of hints, where the last hint is often called a "bottom-out hint" because it contains very specific information that is necessary to solve the problem [190].

Help-aversion— Another noteworthy suboptimal behavior identified in tutoring environments that impacts learning is help-aversion [7]. Help-averse behavior typically involves the lack of use of help features in a learning environment when it is likely to benefit the learner. In most interactive learning environments, there are help features built into the system, for example, in the form of a button on the screen, where the user can request help when needed. Help-aversion is typically observed when the student makes many incorrect attempts but ignores the help button altogether, ultimately failing to utilize the help available to them from the tutoring system.

Because these suboptimal help-seeking behaviors demonstrate lack of use of SRL behavior, we believe that the use of unproductive help-seeking behavior has a relationship to a child's motivation in learning. In this work, we explore this relationship between motivation in learning and suboptimal help-seeking behavior and evaluate how these behaviors can impact learning outcomes through an empirical user study involving a robot tutoring system.

There has also been a number of systems from the ITS community that have highlighted the importance of learner motivation and engagement during learning [22,29,31,49,58]. For example, Clement et al. demonstrates the importance of personalizing tutoring activity selection in a way that maintains learner motivation by providing a student with activities of the right difficulty or challenge [49]. Additionally, ITSs have modeled students' usage of meta-cognitive strategies, effective use of the learning system, and problem-solving strategies [45, 133, 190, 225]. The inclusion of these user-centric attributes and internal states allows tutoring systems to model the broader learning process to better promote effective learning across a diverse population of learners. Our work explores the role of robots as physically embodied tutoring agents and seeks to understand whether robot tutors can be used to shape behaviors and promote learning gains over time.

5.3 User Study: Shaping Productive Help-Seeking Behavior

To illustrate the linkage of motivation in learning, observable behavior within a learning environment, and learning gains (Figure 5.2), we here present empirical evidence from a user study involving children interacting with a robot tutoring system over multiple sessions [180]. We first introduce the context for and the robot tutoring system utilized in this user study. We then describe our experimental design, conditions, and procedure, as well as measures for evaluation and participants.

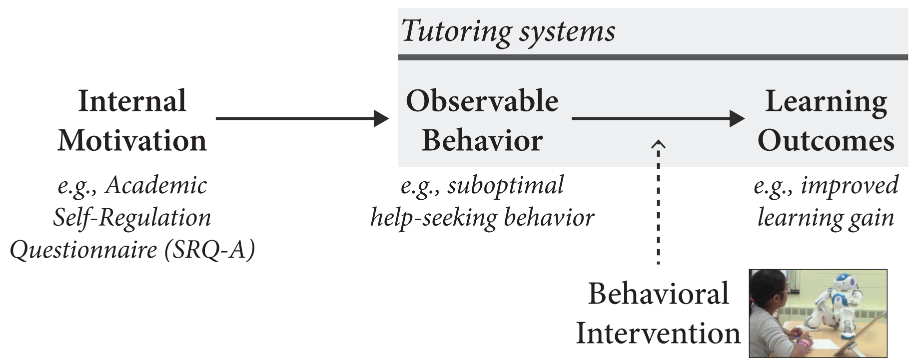

Figure 5.2: Linkage between internal motivation, observable behavior, and learning outcomes. We utilize empirical evidence from a user study to establish a relationship between measures of internal motivation (as measured by a self-report questionnaire) and observable behaviors during a tutoring interaction with a robot. We further show that a robot tutoring system that provides behavioral intervention based on this observable behavior leads to learning gains.

5.3.1 Study Context

We contextualized our study in a robot-child tutoring interaction involving four one-on-one sessions, spanning approximately two weeks (Figure 5.3). The study was conducted in local elementary schools in Connecticut, USA. Given the recent body of work discussed in Chapter 2 indicating that physical robots make promising tutoring agents due to the increased engagement and compliance they foster [17, 168, 173, 227], we chose a physically-embodied robot to act as the tutor in our user study. Throughout the tutoring sessions, a robot acted as a tutoring agent that helped participating children solve math problems (Figure 5.1). In particular, the robot tutoring system was designed to provide hints as requested by the student on how to solve the math problems. In this study, we sought to (1) understand how children's motivation in learning was related to their help-seeking behaviors and (2) evaluate how the robot's help-seeking intervention strategies may shape children's suboptimal help-seeking behaviors and subsequently influence their learning outcomes.

5.3.2 Robot Tutoring System

We built an interactive robot tutoring system consisting of a NAO robot to act as the tutoring agent and a tablet to display the tutoring application containing math problems (Figure 5.1). The math problems were displayed and completed on the tablet positioned in

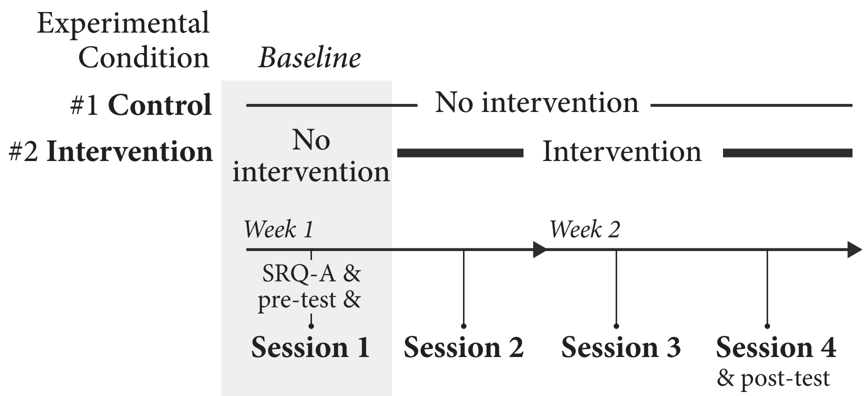

Figure 5.3: Experimental design for the four-session robot-child tutoring interaction study we conducted. Baseline help-seeking behavior for both groups was assessed during Session 1, where neither group received intervention behaviors from the robot. The intervention group received intervention strategies from the robot during Sessions 2 through 4. Children in both groups completed the four tutoring sessions over the course of two weeks.

front of the students. Each of the four sessions contained eight math problems on fractions concepts. All problems followed state curriculum standards, and were designed for students in fifth or sixth grade.

The robot provided verbal feedback on a child's answer to a math problem. For example, it used phrases such as "great job!" for a correct answer and "give it another shot!" for an incorrect answer. Additionally, the robot verbally provided hints at the child's request via the tutoring application on the tablet. Each problem had exactly three hints associated with it and the hints had to be requested in order although they could be repeated. Each successive hint provided more information; the third hint contained the most information relevant to the given problem.

The robot operated autonomously in real-time with each child, requiring no input or intervention from the experimenter throughout the duration of each interaction. It reacted exclusively to tablet input from the child throughout the course of the tutoring sessions. The robot's behaviors were designed to be consistent across all participants over all sessions.

5.3.3 Experimental Design and Conditions

As described in Section 5.2, suboptimal help-seeking behaviors have been identified to impede effective learning with intelligent tutoring systems (ITS) [7]. In this work, we aimed to understand how these behaviors are related to a student's motivation in learning and how a robot tutoring system can effectively intervene in response to these behaviors to improve learning outcomes. To this end, we employed the Academic Self-Regulation questionnaire (SRQ-A), detailed in Section 5.3.4, to measure a student's motivation in learning prior to the beginning of the first tutoring session. We designed a between-subjects experiment in which participating students were randomized into one of two conditions: *control* (participants utilize on-demand help with the robot) and *intervention* (participants received intervention strategies from the robot). We chose to use a repeated measures design to examine behavior change and learning gains of the participants over time. We established each child's baseline behavior during the first session, without introducing the confound of the robot's shaping strategies. Figure 5.3 illustrates the study design.

One established way of providing help in a learning environment is to allow the student to utilize on-demand help. On-demand help refers to help provided by the learning environment that must be actively solicited by the learner [10]. Participants in the control condition relied on the buttons on the tablet interface (pictured in Figure 5.1) to make up to three help requests per question to the robot whenever they wanted to during each session, thereby utilizing on-demand help features of the application.

Participants in the intervention condition followed this same method of requesting help; however, the robot also employed two strategies informed by the literature aimed at countering suboptimal help-seeking behavior, namely *help aversion* and *help overuse* [7,23]. Below we describe the implementation of these two strategies for our robot tutoring system.

- $\mathbf{S_1}$: If the participant makes two consecutive incorrect attempts on a problem without asking for any hints, the robot will automatically provide the participant with the next hint they have not yet requested.
- $\mathbf{S_2}$: If the participant makes three consecutive hint requests on a problem without an attempt in between, the robot will deny the participant the third hint, and request that the participant attempts the problem before asking for more help.

While triggering $\mathbf{S_1}$ may not indicate that the participant was completely help-averse, the behavior involved was still considered suboptimal in our tutoring context. This trigger indicated that the participant was not using the help features of the tutoring system in the most productive way. $\mathbf{S_2}$ is a strategy used to counter the suboptimal behavior of making successive hint requests to receive the most information before attempting the problem. This trigger indicated that the participant was not trying to utilize the information presented in previous hints. Asking the student to make an attempt before requesting more help can encourage the participant to make a bigger effort to understand and utilize the presented hints. These are not the only suboptimal help-seeking behaviors that can be defined in this tutoring context and the absence of these two suboptimal behaviors does not represent optimal help-seeking behavior across all students. Other suboptimal help-seeking behaviors can be measured by how help requests are distributed through time within and across sessions, however, we did not attempt to quantify these or design intervention strategies to counter these types of behaviors in this study. We chose two suboptimal help-seeking behaviors that were based on frequencies of behaviors representing help-aversion and help overuse within our tutoring context that could be easily detected during each question. This led to the design of the simple shaping strategies that can directly counter these behaviors to shape more productive help use over time.

Because these two suboptimal behaviors specifically related to help use during a tutoring session have been shown to impact learning, we hypothesized that building simple robot shaping strategies to directly counter each of these behaviors would lead to improved behavior and learning regardless of "why" students engaged in these behaviors. These particular strategies were derived from countering using "too much" or "too little" help in the context of the robot tutoring interaction we designed. Though we planned to analyze whether suboptimal help-seeking behaviors relate to a child's self-reported academic motivation, we did not measure this relationship before conducting the multi-session user study. Rather than try to classify a child's motivational state based on their use of suboptimal help-seeking behavior, we investigate whether a robot can effectively shape suboptimal use of the help features in our tutoring system. We then further attempt to elucidate whether a child's motivation in learning is related to their use of suboptimal help-seeking behaviors in order to provide a broader understanding for why shaping these behaviors may lead to more effective learning within tutoring.

5.3.4 Measures

In this section, we describe the Academic Self-Regulation questionnaire (SRQ-A) and the measures we used to assess the relationship between students' motivation in learning and their suboptimal help-seeking behavior observed in Session 1 (baseline). We then report the metrics we use to evaluate the effectiveness of the robot employing help-seeking intervention strategies from Session 2 to Session 4.

The Academic Self-Regulation Questionnaire (SRQ-A)

The SRQ-A explores why children complete their school work and is designed for children in late elementary school and middle school [195]. The questionnaire asks children to explicitly consider reasons for completing academic tasks that they are familiar with, such as homework. There are four main questions on the SRQ-A, each requiring responses to eight individual items, making 32 items in total. Each response required is on a four-point scale: "very true" is scored as four, "sort of true" is scored as three, "not very true" is scored as two, and "not true at all" is scored as one. Each of the 32 responses is associated with one of four subscales, which are categories of reasons for academic achievement: external, introjected, identified, and intrinsic. Ryan and Connell define the four categories of reasons as follows: "*External* reasons were those where behavior is explained by reference to external authority, fear of punishment, or rule compliance. *Introjected* reasons were framed in terms of internal, esteem-based pressures to act, such as avoidance of guilt and shame or concerns about self- and other-approval. *Identifications* were captured by reasons involving acting from one's own values or goals, and typically took the form of 'I want.' Finally, and where applicable, we included *intrinsic* reasons for action where the behavior is done simply for its inherent enjoyment or for fun." [195]. An example of one of the four main questions on the questionnaire is: Why do I do my homework? This question is followed by eight reasons, each for which the student would circle one of the four options on the scale indicating the extent of their agreement with that particular reason. The external category is associated with reasons like "because I'll get in trouble if I don't." A reason representing the introjected category is "because I want the teacher to think I'm a good student." An example of a reason that fits identification is "because it's important to me to do my homework." Lastly, "because it's fun" is an example that corresponds with intrinsic reasons for action. The four subscales are organized in order from external to internal orientation towards why they complete school-related activities. Of these four subscales, the *external* category measures externally-oriented motivation, while the other three categories—*introjection*, *identification*, and *intrinsic* motivation—can be grouped under the broader category of internal motivation. The ordering of the subscales indicates that identification is more internal than introjection, and the intrinsic category is considered to be the most internal category of motivation on this scale. The *introjected* category of motivation does include reasons for behavior involving the approval of others, which appears to be an example of external motivation, however it also includes reasons such as "because I will feel really proud of myself if I do well" and focuses on behaving according to internal pressures, allowing the introjected category to be considered somewhat internally-oriented. *Identified* reasons for academic behavior reflect a strong internal value on learning, which is considered to be a positive source of motivation and also allows for identification to be considered internal. Scores for each subscale are calculated by averaging the values of the responses that correspond with each category of reasons.

While there are multiple ways of utilizing the SRQ-A (e.g., combining the four subscales into one score), we chose to treat the subscales separately, because the subscales are not mutually exclusive. For example, a student can score highly on both external and intrinsic subscales. The high internal consistency for the external (9 items, Cronbach's $\alpha = .813$), introjected (9 items, Cronbach's $\alpha = .885$), identified (7 items, Cronbach's $\alpha = .792$), intrinsic (7 items, Cronbach's $\alpha = .874$) subscales confirmed their reliability. The average scores across all participants for each of the four subscales are as follows: $M = 3.07$, $SD = .57$ (external); $M = 3.08$, $SD = .59$ (introjected); $M = 3.51$, $SD = .45$ (identified); $M = 2.68$, $SD = .62$ (intrinsic).

Help-seeking Behavior Change

To evaluate the effectiveness of the robot intervention of suboptimal help-seeking behavior, we counted the number of times strategies $\mathbf{S_1}$ and $\mathbf{S_2}$ would have been triggered for each participant i for a given session S:

$$num\_triggers(i, S) = num\_auto\_hints(i, S) + num\_denied\_hints(i, S)$$

This count involves num_auto_hints, representing the number of times a hint would be automatically given, and num_denied_hints, representing the number of hints that would be denied. We calculate $num\_triggers(i, S)$ for each participant where $S = 1$ and $S = 4$. This metric represents the number of suboptimal help-seeking behaviors observed for a participant in Session 1 (baseline help-seeking behavior) and in Session 4. We further define $\Delta_{triggers}$ as a metric that captures the difference between number of triggers from Session 1 to Session 4 for participant i:

$$\Delta_{triggers}(i) = num\_triggers(i, 4) - num\_triggers(i, 1)$$

We employ this metric to understand the change in a participant's use of their help-seeking behavior.

Learning Gains

In this user study, we investigated a specific learning outcome, learning gains, to measure each student's improvement in knowledge from before to after the tutoring interactions. To assess how the robot intervention may influence a student's learning outcomes, particularly learning gains, we asked participants to complete a pretest before Session 1 and a posttest after Session 4. Participants completed the pretest on the same day as Session 1 and the posttest on the same day as Session 4. Both the pretest and posttest consisted of eight questions each, containing the same types of problems that were presented during the four tutoring sessions. The questions on both pretest and posttest were almost identical, with differing numbers within each problem. We scored both tests by awarding one point for each correct answer and dividing the number of correct answers by the total number of questions, resulting in scores ranging from zero to one (accuracy). The difference in test scores between the pretest and the posttest, Δ_{score}, is a within-subjects measure of learning gains over the

Table 5.1: Participant demographic information for the two experimental conditions in our user study.

Condition	N	Age	Gender	Pretest accuracy	Ethnicity				
					Asian	Caucasian	Hispanic	More than one	Did not report
Control	15	M=10.9 SD=.80	8 males 7 females	M=.51 SD=.27	13.3%	60.0%	13.3%	6.7%	6.7%
Intervention	14	M=10.68 SD=.54	8 males 6 females	M=.31 SD=.29	7.1%	78.6%	0.0%	7.1%	7.1%

course of the entire experiment. All measures of learning gains are calculated relative to each participant's individual pretest score. In our assessment, we employ *normalized learning gain* as defined below for each participant i, allowing us to control for individuals starting at different levels of expertise.

$$\Delta_{score}(i) = \frac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{1 - score_{\text{pre}}(i)}$$

5.3.5 Procedure

Both parent and child consent forms were obtained for each student prior to their participation in this study. Participants were escorted from their classrooms by the experimenter. Before Session 1, each child was introduced to the robot. The robot greeted the participant, saying "Hello! My name is Nao, your personal robot tutor. I'm really excited to meet you and work on some problems together." After this introduction, the participants completed a pretest and the SRQ-A questionnaire addressing why they do certain school-related activities. They then completed four distinct tutoring sessions with the robot, spaced over approximately two weeks. Upon finishing Session 4 of the tutoring interaction, participants completed a posttest. Each child was then given stickers and pencils for participating in the study and was escorted back to their classroom by the experimenter.

5.3.6 Participants

The participants in this study were fifth and sixth grade students from local public schools in Connecticut, USA. A total of 33 students were recruited; however, four participants were excluded from our data analysis (three for not completing the study due to school absences, and one for non-compliance). Table 5.1 displays the demographic information for both the control and intervention groups. Of the 29 students included in our data analysis, 15 and 14 participants were in the control and intervention conditions, respectively. In the control group, there were eight males and seven females with a mean age of 10.9 years ($SD = .80$). The ethnicity of each participant was reported by parents: 13.3% Asian, 60.0% Caucasian, 13.3% Hispanic, 6.7% reported more than one ethnicity, and 6.7% did not report. The average pretest score of the control group was .51 ($SD = .27$). In the intervention group, there were eight males and six females with a mean age of 10.68 years ($SD = .54$). The ethnicities of the participants as reported by parents were: 7.1% Asian, 78.6% Caucasian, 7.1% reported more than one ethnicity, and 7.1% did not report. The average pretest score of the intervention group was .31 ($SD = .29$). As we did not screen children based on their pretest scores, the randomized distribution of students in each group resulted in a lower average pretest score for the intervention group as compared to the control group. Pretest scores were not statistically significantly different between the two experimental groups: $t(27) = 1.904$, $p = .068$. Furthermore, all measures of learning improvement for participants were calculated relative to each individual participant's pretest score, accounting for differing levels of incoming knowledge. Our two experimental groups were gender-balanced and there were no significant gender differences in pretest score between males ($M = .39$, $SD = .32$) and females ($M = .44$, $SD = .25$), $t(27) = .471$, $p = .641$.

Almost all students utilized the system's help features to some extent in the initial tutoring session. 93.1% of participants requested at least one hint during the first session. Only two students (6.9%) did not request help during this session. During Session 1, students requested on average 9.07 hints ($SD = 6.82$). The average number of hints requested during Session 1 did not significantly differ between the control ($M = 7.20$, $SD = 5.51$) and intervention ($M = 11.07$, $SD = 7.70$) groups, $t(27) = -1.566$, $p = .129$. In addition, we did not find any significant gender differences in the average number of hints requested during Session 1 between males ($M = 10.44$, $SD = 6.99$) and females ($M = 7.38$, $SD = 6.49$), $t(27) = 1.208$, $p = .238$.

Table 5.2: Results of correlation analyses linking suboptimal behaviors occuring in Session 1 to subscales of the SRQ-A. Cronbach's α values for each subscale indicate the reliability of the questionnaire subscales. Participants' number of triggers of suboptimal help-seeking behavior from Session 1 had a negative relationship with the identified category of motivation (Section 5.4.1). Additional results showed that number of fast attempts from Session 1 was negatively correlated to the intrinsic category of motivation (Section 5.4.4).

	Motivation Subscales	Cronbach's α	Average Scores	Pearson Correlation to Suboptimal Help-Seeking Behavior (*num_triggers*) (S1)	Pearson Correlation to Number of fast attempts (S1)
External *Orientation*	**External** *e.g., I'll get in trouble if I don't do my homework.*	.813	M=3.07 SD=.57	r(27) = -.090 *p = .643*	r(27) = -.064 *p = .740*
Internal *Orientation*	**Introjected** *e.g., I want the teacher to think I'm a good student.*	.885	M=3.08 SD=.59	r(27) = -.321 *p = .090*	r(27) = -.162 *p = .402*
	Identified *e.g., It's important to me to do my homework.*	.792	M=3.51 SD=.45	**r(27) = -.370** ***p = .048****	r(27) = -.326 *p = .084*
	Intrinsic *e.g., I do my homework because it's fun.*	.874	M=2.68 SD=.62	r(27) = -.24 *p = .211*	**r(27) = -.376** ***p = .045****

5.4 Results

In this section, we provide empirical findings that demonstrate how motivation closely relates to behavior during learning, which in turn can be effectively shaped by a robot tutoring system to improve learning outcomes. We first present results on the relationship between a student's motivation in learning as assessed by the SRQ-A and the occurrence of their suboptimal help-seeking behaviors during the tutoring interaction with the robot. We then show how the robot's intervention strategies impact changes in the number of suboptimal help-seeking behaviors ($\Delta_{triggers}$) and test scores (Δ_{score}) for each individual participant. Additionally, we identified another suboptimal behavior that relates to a student's motivation in learning, further demonstrating the opportunity for robot tutoring systems to leverage observable behavior to drive tutoring intervention behavior. All statistical tests reported below employed an α of .05 for significance. We used non-parametric statistical tests when needed based on the distribution of our empirical data.

5.4.1 Relationship Between Motivation and Suboptimal Help-Seeking Behaviors

In exploring the relationship between students' motivation in learning and their suboptimal help-seeking behavior, we focused on correlations between the SRQ-A subscales and the baseline help-seeking behavior assessed in Session 1 of the user study (see Table 5.2). The baseline help-seeking behavior was represented as $num\_triggers$ defined in section 5.3.4. We consider these two suboptimal behaviors together as they both relate specifically to suboptimal use of the hints in the tutoring system and were the two behaviors we designed strategies for our robot tutor to counter in our user study prior to this analysis. The average number of triggers of suboptimal help-seeking behavior ($num\_triggers$) for students in Session 1 was 2.90 ($SD = 2.51$). There were no significant gender differences in the average number of triggers between males ($M = 3.44$, $SD = 2.45$) and females ($M = 2.23$, $SD = 2.52$) in Session 1, $t(27) = 1.302$, $p = .204$. There were also no significant differences in the baseline number of triggers from Session 1 between the control ($M = 2.07$, $SD = 2.66$) and intervention ($M = 3.78$, $SD = 2.08$) groups, $t(27) = -1.929$, $p = .064$.

Across 29 participants, we found that the frequency of suboptimal help-seeking behavior in Session 1 is negatively correlated with the *identification* subscale of the SRQ-A, $r(27) =$ -.37, $p = .048$ (Pearson correlation). This negative correlation indicates that higher scores on the identification subscale of the SRQ-A correlate with a lower number of suboptimal help-seeking behaviors. The identification subscale captures motivation driven by one's own values and goals and corresponds to reasons on the questionnaire such as "because it's important to me" and "because I want to understand the subject." This finding suggests that children who feel motivated to complete work due to internally viewing it as important are less likely to engage in suboptimal help-seeking behaviors, such as asking for all available hints consecutively or not requesting available help. One potential explanation for this finding is that those who score highly on the identification subscale of the SRQ-A are motivated to expend effort throughout the learning interaction and tend not to avoid help or rely too heavily on help features in the tutoring environment.

This finding shows how motivational factors can be linked to observable behaviors in a

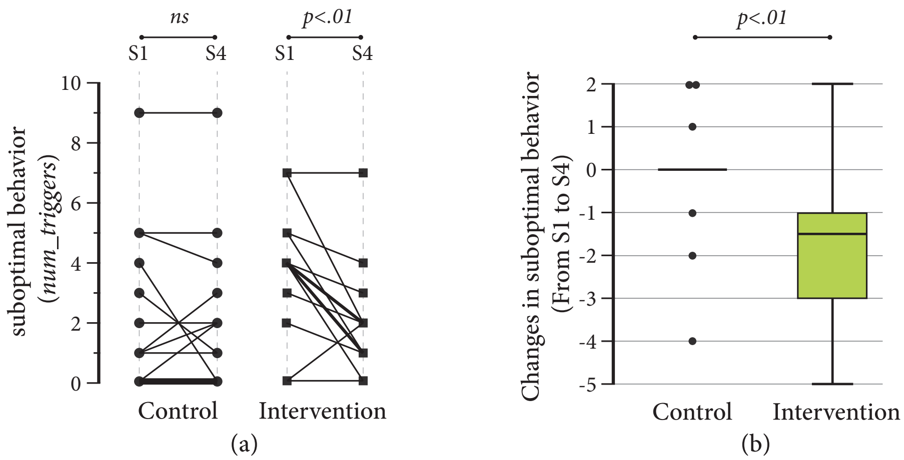

Figure 5.4: Results for behavior change indicate that participants in the intervention group significantly decreased their suboptimal help-seeking behaviors from Session 1 to Session 4, as well as decreased these behaviors significantly more than the control group. (a) Number of suboptimal behaviors, as captured by $num\_triggers$, from Session 1 and Session 4 for each participant in the two experimental conditions. Thicker lines represent multiple participants with the same values. (b) Change in $num\_triggers$ for participants in each group. In the boxplot, the darker line inside the box represents the median, and the extents of the box represent the first and third quartiles. Because of the large number of participants with no difference in suboptimal behavior from S1 to S4 in the control group, the first and third quartiles and the median for the control group are all zero, resulting in the flat box. Remaining data points are shown as points (outliers) due to control group data having IQR=0.

learning environment. It provides evidence showing that internal values towards a learning task can substantially influence a person's suboptimal behaviors during a learning interaction. Next, we demonstrate that creating shaping strategies that directly counter these suboptimal behaviors over multiple tutoring interactions led to fewer occurrences of these undesirable behaviors and greater learning gains.

5.4.2 Help-Seeking Behavior Change

Figure 5.4 summarizes the results of behavior change from Session 1 to Session 4 for the participants in the two experimental conditions. A Wilcoxon Signed-ranks test showed that participants in the intervention group exhibited significantly fewer number of suboptimal behaviors in Session 4 (Mdn = 2.0, $IQR = 1$) than they did in Session 1 (Mdn = 4.0, $IQR = 2$), Z = -2.605, p = .009. Conversely, we did not see such improvement in the control group; there was no significant difference in the number of suboptimal behaviors participants in

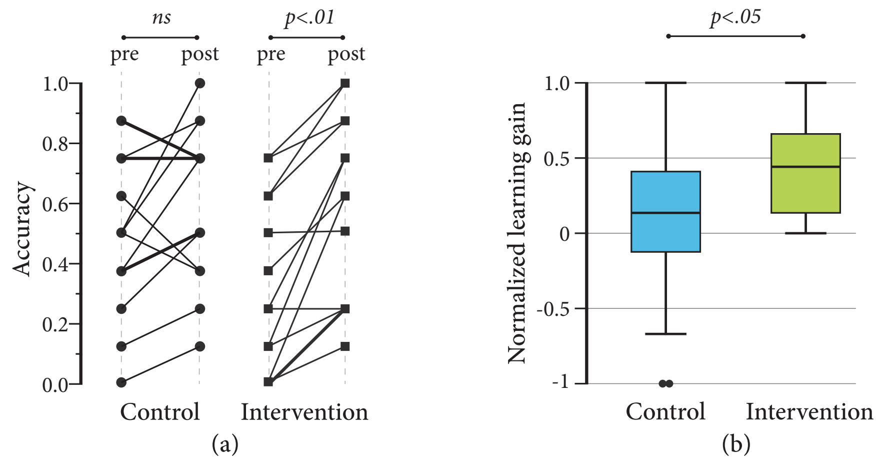

Figure 5.5: Results for learning gains demonstrate that participants in the intervention group significantly improved their scores from pretest to posttest, as well as improved their score significantly more than the control group, as measured by normalized learning gain. (a) Pretest and posttest scores for each participant in the two experimental conditions. Thicker lines represent multiple participants with the same scores. (b) Normalized learning gain for participants in each group. In the boxplot, the darker line inside the box represents the median, and the extents of the box represent the first and third quartiles.

the control group (using on-demand help) exhibited in Session 1 (Mdn = 1.0, IQR = 4) and Session 4 (Mdn = 1.0, IQR = 3), Z = -.213, p = .832 (Wilcoxon Signed-ranks test). Moreover, the decrease in number of triggers, $\Delta_{triggers}$, was significantly greater for the intervention group (Mdn = -1.5, IQR = 2.0) than for the control group (Mdn = 0.0, IQR = 0), indicated by a Mann-Whitney test, U = 45.000, p = .008.

Together, these results demonstrate that the robot's intervention strategies aimed at shaping productive help-seeking behavior were successful in mitigating the occurrences of suboptimal help-seeking behaviors over time. Participants in the intervention condition significantly decreased their number of suboptimal help-seeking behaviors over time while participants in the control condition did not. Though the behavior change we observed may be a short-term effect, we did observe more productive help-seeking behavior over the course of the two weeks, indicating the effectiveness of the intervention strategies in the duration of time students interacted with the robot.

5.4.3 Learning Gains

Figure 5.5 summarizes the results for learning gains for the participants in the two experimental conditions. For participants that received the help-seeking intervention strategies, posttest scores (Mdn = .62, $IQR = .63$) were significantly higher than pretest scores (Mdn = .25, $IQR = .63$), $Z = 3.089$, $p = .002$ (Wilcoxon Signed-ranks test). On the other hand, for participants in the control group that did not receive intervention strategies, there was no significant change in score from pretest (Mdn = .50, $IQR = .38$) to posttest (Mdn = .75, $IQR = .38$), $Z = 1.615$, $p = .106$ (Wilcoxon Signed-ranks test). We further sought to understand differences in normalized learning gains between groups. An independent samples t-test revealed that participants in the intervention group ($M = .45$, $SD = .34$) improved their score from pretest to posttest significantly more than those in the control group ($M = .06$, $SD = .59$), $t(27) = -2.169$, $p = .039$.

These results show that participants receiving intervention strategies from the robot were able to improve their test scores effectively, while the group that relied on using on-demand help were not. These results, together with the results of behavior change from the previous section, indicate that the shaping strategies employed by the robot improved help-seeking behaviors, which thereby positively impacted learning outcomes for participants.

5.4.4 Additional Findings: Relationship Between Motivation and Fast Attempts

Thus far, we have provided empirical findings illustrating the linkage of motivation, behaviors, and outcomes in a learning scenario where children practiced math problems with a tutoring robot. In particular, we have shown that internal motivation, especially *identification*, were negatively correlated to suboptimal help-seeking behaviors during learning, and that the robot tutoring system effectively intervened in response to the undesirable help-seeking behaviors to improve behavioral and learning outcomes. Our findings of the linkage of motivation, behaviors, and outcomes in learning encouraged us to explore different dimensions of suboptimal learning behaviors that robot tutoring systems hold potential to address through effective intervention strategies. Below, we report on a further analysis of our present data revealing the relationship between another internal factor of motivation, namely *instrinsic* motivation, and the suboptimal behavior of *fast attempts* (consecutive incorrect attempts within a small time frame). These results are also displayed in Table 5.2.

Another undesirable behavior we observed in the tutoring interactions was children making successive attempts in a small window of time as if they did not make enough effort to work out the problems presented, indicating the likelihood of guessing. We considered such behavior as fast attempts and defined $num\_fast\_attempts$ as the number of attempts made within a small threshold of seconds (empirically determined to be 20 seconds) from the previous attempt. This behavior is considered to be suboptimal in this learning interaction, as the questions given to the students were on fractions and contained multiple steps to complete, meaning that a successive attempt within a few seconds of an incorrect attempt does not give the student adequate time to rework the problem. The average number of fast attempts ($num\_fast\_attempts$) for the 29 students in Session 1 was 2.79 (SD = 4.77). We did not consider fast attempts in advance when designing our robot shaping strategies for the user study we conducted, in which we specifically designed shaping strategies for suboptimal behavior specifically relating to hint use in the system. Because the robot did not actively track and counter this behavior, we consider it separately from our measure of suboptimal help-seeking behavior.

In exploring the relationship between motivation and the behavior of fast attempts, we found that $num\_fast\_attempts$ is negatively correlated with the *intrinsic* motivation subscale on the SRQ-A, $r(27)$ = -.38, p = .045 (Pearson correlation). The intrinsic motivation subscale on the SRQ-A corresponds to reasons for doing various types of school work for implicit enjoyment in learning and completing work. Scoring highly on this subscale may indicate a tendency to put effort into each attempt, even after an incorrect attempt, thereby making less “guessing” attempts. We further found that $num\_fast\_attempts$ is negatively correlated with posttest score, $r(27)$ = -.47, p = .011 (Pearson correlation), although we did not include shaping behaviors aimed at countering fast attempts in our user study. This negative correlation dictates that higher posttest scores correspond with a lower incidence of fast attempts in Session 1 (baseline). This finding suggests an opportunity for designing robot intervention aiming to shape the suboptimal behavior of fast attempts to improve learning outcomes.

5.4.5 Discussion

The results of our user study demonstrate the linkage of motivation, behaviors, and learning outcomes that underlies learning processes (Figure 5.2). We employed the Academic Self-Regulation Questionnaire (SRQ-A), involving four motivational factors including *external*, *introjected*, *identified*, and *intrinsic*, to assess children's motivation in engaging in learning tasks. We found a negative correlation between the *identified* factor of motivation and the suboptimal behavior of help-seeking (e.g., help-averse and help overuse behaviors), as well as a negative correlation between the *intrinsic* factor of motivation and the suboptimal behavior of fast attempts. Moreover, we demonstrated that a robot tutoring system can employ help-seeking intervention strategies effectively to reduce the suboptimal behavior of help-seeking and to improve learning gains. We also note that the correlations between the *introjected* factor of motivation and suboptimal help-seeking behaviors were marginally significant (Table 5.2). The *identified* category of motivation showed a marginally significant correlation to the suboptimal behavior of fast attempts as well. This aligns with our results as each of these three categories of motivation are grouped together as internally-oriented, indicating that these more positive sources of motivation all correspond to a lower incidence of suboptimal behaviors. However, not all categories of motivation with an internal orientation were correlated to the behaviors measured during the tutoring sessions. For example, we did not see a correlation between intrinsic motivation and the suboptimal help-seeking behaviors despite intrinsic motivation being the most internally-oriented subscale of motivation. While we cannot be sure about why this is, this may be a limitation of our smaller sample size. Alternatively, it may be the case that certain behaviors, such as help-seeking behaviors, correlate more strongly with specific measures of internal motivation. Additional research is required to understand which sub-categories of internal motivation may prove most informative in the context of our motivation-behavior-learning outcomes pipeline. Similarly, the external category of motivation, which is considered to be a less positive source of motivation in learning, did not significantly correlate to our measures of suboptimal help-seeking behaviors or fast attempts. Though a student's external motivation may still be useful to understand within a learning context, our empirical results indicate the value of understanding suboptimal behavior in relation to categories of internally-oriented motivation.

Participants who reported a lower level of identified regulation were the ones who had higher levels of baseline suboptimal help usage. As higher identified regulation indicates agreement with reasons involving an internal sense of importance for completing academic work, this suggests that motivation in learning can influence how a student utilizes resources in a learning environment, such as the help features of the system. Our results on behavior change and learning gains lead us to believe that shaping these unproductive help-seeking behaviors during a learning interaction can cause students to engage more effectively with a robot tutoring system, thereby impacting their learning outcomes over time. Together, these findings add a broader lens on why a robot shaping suboptimal help-seeking behavior was effective in promoting learning.

Through this process, we introduced a basic approach for designing robot intervention, which involves finding observable behaviors that correspond to motivational factors, and employing a robot to respond to these behaviors to create more effective tutoring interactions. In further exploring this approach, we identified an additional observable behavior that had a relationship to a measure of intrinsic motivation. Similarly to suboptimal help-seeking behavior, students who had lower intrinsic motivation as measured by the SRQ-A made more fast attempts, indicating that lower intrinsic motivation manifests itself during learning through suboptimal behaviors that can be monitored by a robot tutoring system. Because students' use of these fast attempts correlates negatively with posttest score, this suggests that a robot tutoring system specifically designed to intervene based on this behavior that signals suboptimal use of the system might lead to improved learning.

Prior work in tutoring systems has attempted to take into account a student's motivation in several different ways. Some systems automatically provide exercises or lessons that fit a student's ability, assuming that a student will stay motivated if experiencing the right level of challenge [49, 142]. Other work has sought to increase motivation in learning through game-based environments or has focused on building tutoring environments that enhance student motivation through various strategies such as providing choices or using social support [57, 105, 200]. Our results highlight a simple way to incorporate types of motivation into a learning environment by demonstrating the usefulness of linking measures of motivation with observable behavior within a learning environment, which further lends itself to designing robot intervention behavior that has the potential to foster learning gains. We evaluated our approach in the context of an autonomous robot tutoring system for children; however, we believe this process can also be useful in designing behaviors for a variety of agent-based tutoring systems as well.

The influence of motivation on behavior is certainly not limited to learning outcomes within a tutoring setting. Extensive research has demonstrated how motivation impacts a variety of important health-related outcomes such as physical fitness, smoking cessation, and weight loss [215]. Utilizing an intelligent system to understand how motivation relates to observable behaviors can be leveraged to provide support that will be useful in promoting these types of impactful health outcomes. The design approach we describe in this chapter is not limited to the domain of education, but rather has potential to be applied to improving health-related outcomes as well. Providing empirical support for this design tool demonstrates the feasibility of leveraging the relationship between internal motivation and behaviors to inform the design of intervention behaviors for a supportive robot. Applying a similar process outside a tutoring setting in other application domains in which motivation plays a crucial role should be further explored.

The study described in this chapter employed a setup involving an autonomous robot tutor and an authentic math tutoring context similar to those described in Chapters 3 and 4. This reinforces the empirical validity of our findings. In an effort to move past shorter, one-session studies, this user study spanned four tutoring sessions, allowing us to examine behavior change and learning gains over a longer period of time. It is important to consider longer-term tutoring interactions, as it likely that robot tutors that are deployed in homes and classrooms will be interacting with students for more than a single session. Additionally, as learning is a complex process that does not necessarily happen quickly, longer-term tutoring interactions are important for understanding how a student progresses in terms of behavior and performance over time. Still, our longer-term interaction consisted of four sessions spaced out over approximately two weeks. Robot tutoring systems must be built to interact with children in real-world settings such as classrooms and homes for much long periods of time and should be designed robustly to successfully engage their users during these extended deployments. Furthermore, it is of particular importance in the application of tutoring to understand whether learning gains and behavior change as a result of robot intervention during tutoring lasts over time and yields robust learning.

Though the work presented in this chapter demonstrates the promise of linking motivation in learning, behavioral intervention, and learning outcomes to inform the design of effective robot tutoring systems for children, there are some limitations that should be acknowledged. The correlations we observed between certain subscales of motivation and suboptimal behaviors during tutoring were not strong, which may have been a consequence of trying to relate measures capturing intricate constructs such as motivation types to more simple actions within a learning environment, such as requesting three hints in a row. We did not utilize these correlations to classify a child's internal motivational state, but rather presented empirical evidence supporting the presence of a relationship between measures of complex categories of motivation to reliable, observable behaviors within an automated learning environment. Nonetheless, future research should investigate linking measures of motivation to observable behavior and designing robot behavior accordingly with a much larger population to more thoroughly evaluate the validity of this approach.

We focused on identifying observable behaviors that could be detected reliably during the learning interaction, and relied on features that could be collected from the child's input using the tablet device. However, given other related work investigating the use of sensor-based approaches to understand information about the user (such as attention through EEG [216], or engagement through facial feature detection [87, 135]), future work should leverage these channels of information to understand how these richer features relate to a student's motivation in learning as well. Our work also relied on self-reported questionnaire data (SRQ-A) to measure a child's motivation for completing academic work. Though this was a validated questionnaire designed to be used by children, not all children excel at accurately assessing themselves, especially at a meta-cognitive level. It would also be beneficial to consider other measures of a child's motivation in learning from adults who have interacted with them for a longer period of time, such as parents or teachers.

5.5 Summary

Behaviors related to motivational attributes, such as help-seeking behavior, are important factors in successful tutoring interactions. Leveraging the intuitive idea that motivation relates to observable behavior, which in turn relates to learning outcomes, we describe a pipeline that facilitates an approach to designing robot intervention behaviors during learning. If a robot monitors observable behavior within the tutoring environment, and intervenes when unproductive behavior is detected, this can enhance the effectiveness of the learning interaction over time. We validated this framework for the design of robot behavior by investigating whether a robot tutor that uses shaping strategies to counter unproductive help-seeking behaviors impacts learning and behavior. We found that certain unproductive behaviors correlate to measures of internal motivation, and that our robot tutor was successful in reducing suboptimal help-seeking behavior and improving learning gains over the course of a longer-term tutoring interaction.

These findings lend themselves to the design of intelligent intervention behaviors for robot tutoring interactions. For example, if someone designing a robot tutor observes that measures of motivation relate to measurable indicators of other salient behaviors, such as boredom during tutoring, the robot can specifically respond to these types of behaviors, which have the potential to enhance learning. Furthermore, the results of our user study highlight some interesting aspects of children interacting with robot tutors. Similar to what has been found in ITS research, we found that students do not always engage in "good" help-seeking behavior on their own, making fully on-demand help systems less desirable when building effective tutoring systems. This is useful information when designing supportive robot tutors, as students require close support to utilize the resources available in the learning environment to their full potential. Furthermore, our findings are in line with our more general design recommendations that responsive behavior intervention from robot tutors has greater potential to enhance learning gains, as opposed to a one-size-fits-all approach.

While this pipeline for designing robot intervention behavior is both intuitive and easy to employ, it still involves finding observable behaviors that occur at least somewhat frequently in tutoring settings and conducting initial analysis to see whether these behaviors correspond to higher-level user states. This is a challenging process that may not always be feasible when deploying robot tutors in real-world settings. The behaviors that are designed via this process may respond to the behavior of an individual student; however, the approach we used in our longer-term user study is still based on looking for the occurrence of the same behaviors across users regardless of their individual performance. In the next chapter, we move towards a more general model that allows the robot to provide help to a student during a tutoring interaction on a cognitively challenging subject in a way that is more personalized to the individual. We develop a computational model that dictates how the robot should help the student that leverages many of the design recommendations from our studies detailed in Chapters 3-5 and explore whether our model is effective in providing personalized help to students in a long-term tutoring setting.

Chapter 6

Modeling Help Action Selection in Robot-Child Tutoring*

As we move toward long-term tutoring interactions, robot tutors must employ strategies to provide different types of help and support to students as they need it over time. This means that we must select tutoring behaviors that address different goals such as providing rest, promoting self-efficacy, and supporting metacognitive strategy use while also proactively providing different levels of help to students of different competency levels. A more robust model of how to balance these helpful tutoring actions is necessary when building an autonomous tutoring system that students interact with over longer periods of time. If a robot tutor can maintain informative state information about the student's knowledge and engagement levels, they may be able to make intelligent decisions on what help to provide that meets the student's needs and fosters effective learning over time.

In this chapter, we describe a computational model designed to plan optimal help actions for children during a longer-term tutoring scenario. We detail the design of the model and its empirically-derived parameters and demonstrate a partially observable Markov decision process (POMDP) framework that models the process of providing help to a student during a learning interaction. We formulate the robot-student tutoring help action selection prob-

*Part of the work in this chapter is currently in submission: Aditi Ramachandran, Sarah Strohkorb Sebo, and Brian Scassellati. Personalized Robot Tutoring using the Assistive Tutor POMDP (AT-POMDP). under review. [181]

lem as the Assistive Tutor partially observable Markov decision process (AT-POMDP). We evaluate the effectiveness of AT-POMDP by employing it to provide help to students during a math tutoring task and comparing it to a fixed policy that chooses help actions. Our results show that students who received help actions from AT-POMDP's policy demonstrated increased learning gains when compared to those who received help according to the fixed policy. We show the strength of our computational action selection policy by more closely examining three particular participants and detail how the AT-POMDP policy selected appropriate help actions in each of their cases.

6.1 Introduction

Human tutors are known to be very successful, largely due to their ability to provide different types of assistance and feedback for students [157]. Additionally, they are able to readily understand a student's cognitive abilities, and can balance this with more unpredictable, short-term affect that the student experiences, such as lapses in engagement [141]. We know that robot tutors have been a promising technology to emulate some of the aspects of one-on-one human tutoring. In order for us to understand whether robots can be effective tutors across a diverse set of individuals and over longer interaction periods, it is crucial that we investigate modeling and planning techniques for robots to dynamically provide different types of support to meet the needs of students. For example, if a student needs help understanding a cognitively challenging concept, yet is also disengaged and starting to make guesses instead of earnest attempts, the robot tutor must balance these observations and take actions according to a model that will maximize the student's chances of learning. Building mechanisms that can probabilistically model a student's state and can plan actions under uncertainty to benefit the learner is critical to an effective robot tutor that helps a student over time.

Because this is such a challenging problem, many existing tutoring systems provide on-demand help, allowing the learner to have control and request help as they see fit. As evidenced by prior work in intelligent tutoring systems, students of all ages often do not use these on-demand features effectively, frequently asking for too much help or underutilizing

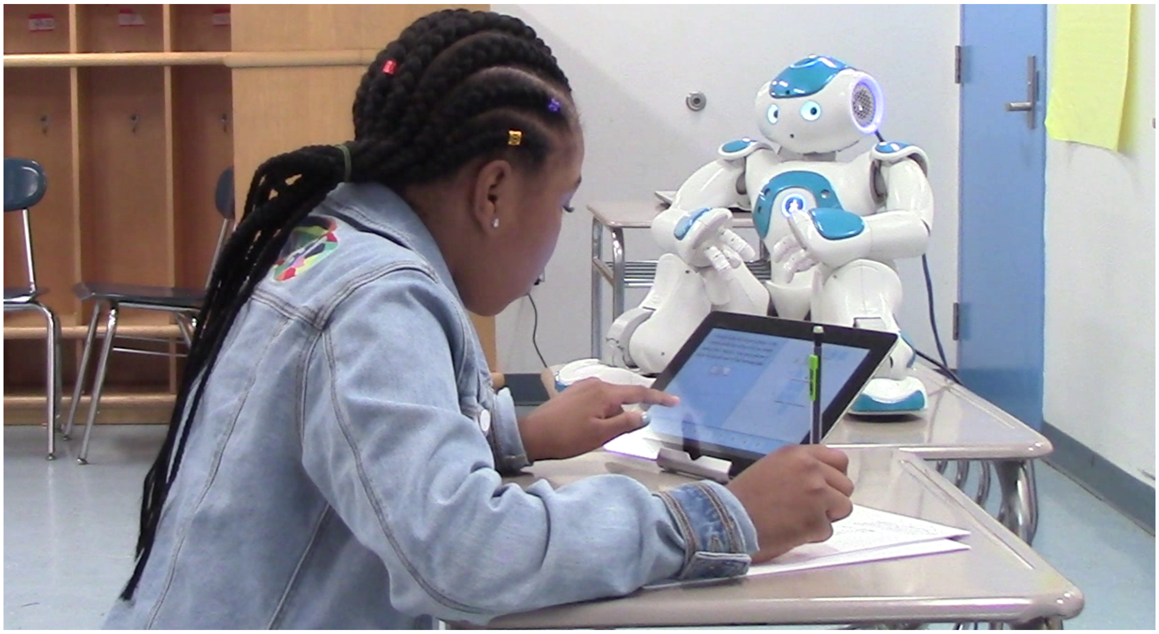

Figure 6.1: A student receiving help from our interactive robot tutoring system. We built a computational model for a robot tutor to employ to provide help strategies to individual students and evaluated the model's effectiveness in supporting students over a multi-session tutoring interaction.

the available help. Young children in particular do not necessarily have the self-regulation skills to seek help productively, which is considered a metacognitive strategy itself. We also know this from our previous study described in Chapter 5, which explored how robots can be useful in shaping more productive help-seeking behaviors in children. Another strategy to manage the potential misuse of help in a tutoring system is to remove the control from the learner and instead allow the robot tutor to proactively provide help and support to children.

Proactively providing support in a personalized manner to students of varying skill levels and attributes is still an open problem for autonomous tutoring systems, especially for younger children who are often unpredictable in learning environments. Choosing which type of help to provide to a student in a variety of different circumstances is not always straightforward. Additionally, if we want to provide personalized support, it is crucial that the robot tutor provides these actions based on salient aspects of the student, like their knowledge level and whether or not they are engaged. Complex user states are not directly observable so these critical decisions must be based on estimates or approximations.

POMDPs provide a general framework within which optimal actions can be planned while maintaining an estimate of the world. In this chapter, we design and build the Assistive Tutor POMDP (AT-POMDP), a model based on the POMDP framework capable of providing support actions to students during tutoring. We describe our model's design decisions and explain our model's empirically-derived parameter choices. We also validate AT-POMDP's effectiveness in decision-making by conducting a user study in which students interact with a robot tutor that employs AT-POMDP to provide support to the students over multiple tutoring sessions (Figure 6.1). We found that the students who received help from AT-POMDP's policy improved learning gains when compared to students who received help from a fixed policy, suggesting the importance of providing personalized tutoring support for young children.

6.2 Background

In this section, we highlight computational approaches to tutoring spanning various types of intelligent tutoring systems (some of which involve a robot) and review work that relates to help action selection for tutoring systems.

6.2.1 Computational Approaches to Tutoring

As detailed in Section 2.2.2 in Chapter 2, there are several approaches to student modeling in intelligent tutoring systems, the most common of which is Bayesian Knowledge Tracing (BKT) [55]. Work dealing specifically with robot tutoring systems have also used approaches based on BKTs [59, 142, 206]. Providing hints based on a BKT model of skill estimation improved learning gains on a puzzle-solving task for adults [142]. Additional work has successfully used a BKT-based approach to tutor language skills for adults and children [59, 206].

There have been other computational approaches to modeling various aspects of the tutoring process, including fuzzy logic, dynamic bayesian networks, and reinforcement learning [32, 46, 51, 86, 213]. Due to the social nature of robot tutors, there have been several efforts in modeling affective behaviors for robot tutors, including empathic behaviors and affective reactions [87, 136]. Recent work has explored employing POMDPs to plan actions in a teaching setting [79, 176]. POMDPs are typically challenging to employ in real-time systems given the large state spaces that arise in teaching tasks [79]. Rafferty et al. used a POMDP approach to find optimal teaching actions during a concept learning task, in which they minimize the expected time for a learner to acquire a new concept in a short interaction. They demonstrate that adults can learn a simple concept faster when receiving teaching actions dictated by the POMDP model versus a random baseline [176]. Our action selection approach uses a POMDP solver to plan supportive help actions to students during a robot-child tutoring task in which students practice a difficult mathematical concept they have learned in school over several tutoring sessions. In addition, our approach considers the learner's engagement rather than just the learner's knowledge level of the given concept.

6.2.2 Help Actions in Tutoring

There are many possible action choices a robot tutor can select in order to support learners during tutoring. For a more detailed discussion of different types of help and feedback used in tutoring systems, see Section 2.2.3 in Chapter 2. Hints are one of the most common types of help used in tutoring systems [5]. Other work has shown the benefits of more extensive forms of help including worked examples and in-depth tutorials [156, 226]. Requests for self-explanations (asking the student to think aloud) have also been found to be a useful strategy for tutoring systems [182]. Our own study described in Chapter 4 showed that thinking aloud can benefit learners.

In addition to help actions that relate to improving mastery of the educational concepts within tutoring, other support mechanisms are employed by intelligent tutoring systems to maintain learner engagement. Many tutoring systems adapt the ordering of exercises to provide content at the right level of challenge, which inherently should keep students engaged [55]. Other robot tutoring systems have looked at strategies to re-engage students if attention is lost [37, 137, 216]. As described in Chapter 3, our own work on mechanisms to maintain engagement during tutoring suggests that providing short, non-tasks breaks to the student based on measures of performance can restore engagement and positively impact learning.

Much of the work on help actions in tutoring systems has focused on identifying useful help strategies rather than understanding how to balance multiple help actions during a tutoring scenario. Our work focuses on planning which supportive tutoring actions to provide to a given student from a bank of actions we identify as potentially helpful to students. We chose the following help actions based on their reported usefulness from prior work in tutoring systems and our own previous user studies: self-explanations, hints, worked examples, tutorials, breaks, and no action (withholding help). Our approach uses a POMDP framework to both maintain an estimate of student knowledge and engagement and provide the best action to maximize the user's progression towards higher knowledge.

6.3 Modeling Tutoring with a POMDP

This section formulates the robot tutor action selection problem as a POMDP called the Assistive Tutor POMDP (AT-POMDP) and describes the model design and parameters. We first describe the generalized POMDP framework that we apply to our tutoring setting. We then present the AT-POMDP formulation that can be used to find a policy to select help actions for students during tutoring. We also cover the parameters we used for our specific instantiation of the model in a real-world tutoring scenario.

6.3.1 POMDP Framework

A partially observable Markov decision process (POMDP) [109] can be represented as a 7-tuple $(S, A, \Omega, T, R, O, \gamma)$, where:

- S is the set of partially observable states with $s \in S$. The state space is defined as the set of all possible states in S.
- A is the set of possible actions with $a \in A$. The action space is defined as the set of all possible actions in A.
- Ω is the set of observations with $o \in \Omega$.
- $T : S \times A \times S \to [0, 1]$ is a probabilistic transition function such that $T(s, a, s') \equiv \Pr(s'|a, s)$, which is the probability that s' follows from taking action a in state s.

- $R : S \times A \times S \to \mathbb{R}$ is a reward function mapping state-action-state tuples to rewards.

- $O : S \times A \times \Omega \to [0, 1]$ is a probabilistic observation function such that $O(a, s', o) \equiv \Pr(o|a, s')$, which is the probability that o is observed after taking action a and ending in state s'.

- $\gamma \in [0, 1]$ is the discount factor.

After each time step, the agent making decisions updates its belief, b, a probability distribution over S, where $b(s)$ represents the belief relative to state s. The belief can be updated according to the following:

$$b'(s') = \eta O(s', a, o) \sum_{s \in S} T(s, a, s') b(s) \tag{6.1}$$

where $\eta = 1/\Pr(o|a, b)$, a normalization term to ensure that $\sum_{s \in S} b(s) = 1$.

The solution to a POMDP is a policy that maps beliefs to actions, $\pi : B \to A$, and selects actions that maximize the value function, or the expected discounted reward.

6.3.2 State Space

The state space of AT-POMDP consists of three dimensions: knowledge level, engagement level, and problem attempt number. There are four domain-independent knowledge levels that roughly equate to: little to no mastery (K1), some mastery (K2), moderate mastery (K3), and near-complete mastery (K4). There are two engagement levels: low and high. High engagement is marked by the students' attention being fully paid to the problem at hand, making honest attempts at the problems. Low engagement is marked by either rapid guessing on problems without knowing the correct answer or boredom and off-task behavior. The state space encodes multiple attempts for each exercise, giving students three attempts per problem. If all attempts on a given problem are answered incorrectly, they will be moved onto the next question. Attempts 1R (after a correct previous attempt), 1W (after an incorrect previous attempt), 2, and 3 are encoded into our state space. With 4 knowledge levels, 2 engagement levels, and 4 attempt types, there are $4 \times 2 \times 4 = 32$ possible states in this state space.

6.3.3 Action and Observation Spaces

The robot's action space consists of help actions that a robot tutor can take to support learners during the tutoring process. Our action space includes 6 tutoring actions, which during the tutoring session are administered when an incorrect attempt is made by the student on a problem. We describe the 6 actions used in our model's implementation in Section 6.4.2.

Observations consist of a student's accuracy and timing on each attempt. These observations are capable of being detected robustly and closely relate to student knowledge and engagement levels. Accuracy is represented as being either correct or incorrect on a given attempt. There are three potential values for the timing component of the observation: slow, medium, or fast. Characterizing a specific attempt time as slow, medium, or fast is determined by comparing the student's time on the current attempt to the student's average timing on prior attempts. Thus, the timing part of an observation is relative to the average timing of the individual student since average attempt timings typically vary greatly between students. The size of the observation space is 2 (correct or incorrect) $\times$ 3 (slow, medium, or fast) $=$ 6 for each attempt made by the student to answer a tutoring problem.

6.3.4 Reward Model

The reward function formalizes the robot tutor's goal of aiding the student to transition from lower to higher knowledge states and to transition from low to high engagement by rewarding those transitions. Each action is also taken with a cost proportional to the time it takes for the student to complete that action (some help actions take longer to complete than others). We also penalized any action other than no-action heavily on the first attempt so that students would always have a chance to answer the question before a help action was chosen and performed by the robot.

6.3.5 Transition Model

The transition model $T(s, a, s') \equiv \Pr(s'|a, s)$ can be derived by examining the likelihood of change in each of the three dimensions of the state space: $\Pr(s'|a, s) \equiv c_a \cdot \Pr(s'_a|a, s) \cdot \Pr(s'_e|a, s) \cdot \Pr(s'_k|a, s)$, where s_a represents the attempt component, s_e represents the engagement level, and s_k represents the knowledge level specified by state s and c_a represents an action-specific constant multiplier, since each action will uniquely influence state transitions.

$\Pr(s'_a|a, s)$ represents the likelihood that a student moves to a particular attempt, given the prior state, which evaluates to the likelihood a student answers a question incorrectly/correctly given their prior state. For example, if a student is on the first attempt of a math problem in the lowest knowledge state, with a 25% chance of answering a question correctly, there is a 0.25 probability that student will answer the attempt correctly and transition to attempt state 1R and there is a 0.75 probability the student will answer the attempt incorrectly and transition to attempt state 2. The probability is 0.0 for the transition of the student from the first attempt of the problem to attempt 1W and attempt 3. Because engagement level also influences whether a student answers a question correctly, we add a multiplier to the probability that the student would answer the attempt correctly, to capture the decreased likelihood of answering correctly while at a low engagement level.

$\Pr(s'_e|a, s)$ represents the likelihood that a student moves from one engagement level to another, either low to high engagement or high to low engagement. The probability depends on knowledge level as well, as a lower knowledge level may indicate a higher likelihood of transitioning from high to low engagement.

$\Pr(s'_k|a, s)$ represents the likelihood that a student moves from one knowledge level to another. In our model, we make the assumption that students can only increase their knowledge level and cannot 'lose' knowledge. These probabilities also depend on engagement level, as gaining knowledge while experiencing low engagement is highly unlikely.

Each action uniquely influences the likelihood of state transitions, namely the likelihood of increasing knowledge level and the likelihood of increasing engagement level. We made increases in knowledge most to least likely for the following actions: interactive-tutorials, worked-examples, hints, and think-alouds. Breaks and no-actions had no differential probability of increasing knowledge level. For engagement increase, we had break be the most likely action to raise engagement level followed by think-aloud, since the think-aloud action requires a verbal response. Interactive-tutorials, worked-examples, hints, and no-actions had no differential probability of increasing engagement level.

6.3.6 Observation Model

Since the state space encodes the attempts and the transition model encodes the possible attempt progressions, the observations of correct and incorrect attempts inform the attempt number with absolute confidence $\Pr(s'_a|s_a, o) = 1.0$, where s_a represents the attempt component of state s. Thus, the observation model is only informed by the likelihood that particular attempt speeds (low, medium, high) are characteristic of low/high engagement levels.

6.3.7 Parameter Selection

Below, we provide a detailed account for the parameters we selected for our instantiation of AT-POMDP. Many of the model parameters were derived from previous robot-child tutoring data we collected, specifically from the user study on shaping productive help-seeking behavior we detailed in Chapter 5. In addition to retrieving timing and accuracy data from the students in this study, we annotated the video data from the students in this study to have a measure of 'ground truth' for observations of students' engagement levels during the tutoring sessions. These parameters may not hold for other tutoring scenarios, including those involving different student populations and different curricula or application domains.

State and Observation Space Parameters— We chose question accuracy levels that roughly correspond to the four domain-independent knowledge levels: little to no mastery ($\sim$ 25% question accuracy), some mastery ($\sim$ 50% question accuracy), moderate mastery ($\sim$ 80% question accuracy), and near-complete mastery ($\sim$ 95% question accuracy). In order to determine the timing component of a given observation for a student (low, medium, or high), we assessed how the timing for the current attempt compared to the student's average time on prior attempts by calculating a z-score, which measures how many standard deviations the current data point is from the mean. We categorized a z-score of less than -1.0 as fast and a z-score of greater than 2.0 as slow. A student's first ten attempts were calculated as medium to establish a baseline for a student's average attempt speed.

Transition Model Parameters— In determining the likelihood that a student makes a correct/incorrect attempt based on prior state, we looked at first attempt accuracy from our collected data. We found that if students were at a high engagement level on the first attempt, attempt accuracy for each knowledge level (1 - 4) was approximately [0.25, 0.50, 0.80, 0.95]. After the first attempt, the students' accuracy scores were lower, given that they had already answered the problem incorrectly once, and for each knowledge level had the following accuracy scores for attempts after the first attempt: [0.15, 0.33, 0.60, 0.90]. Lastly, students who are at a low engagement are less likely to answer the attempt correctly. We observed that students answered attempts correctly when at a low engagement level very infrequently, so the multiplier to the probability that the student would answer the attempt correctly with a low engagement level was set to 0.2.

In estimating the likelihood of a student moving from one engagement level to another, we found that as knowledge level increases, the likelihood of transition from high to low engagement on a particular attempt decreases from a probability of about 0.10 to a probability of about 0.01. However, we discovered that regardless of the knowledge level of the student, students re-engaged (moving from a low to a high engagement state) with about the same probability of 0.33.

After examining how likely students were to gain a knowledge level when at a high engagement level and testing with our system, we set the probability of gaining a knowledge level to 0.02. We set the probability of knowledge level gain when a student is at a low level of engagement to be very low (0.001), since gaining knowledge while disengaged is extremely unlikely.

Observation Model Parameters— From the prior study data, we noted that there was no significant difference between the z-score attempt speeds between students in different knowledge levels, however, we did notice a difference in z-score speeds between students who had low versus high engagement. For engaged students, medium speeds were observed about 90% of the time, where about 5% of engaged students were fast and slow. For disengaged students, medium speeds were observed about 50% of the time, where about 25% of students were fast (blind guessing) or slow (bored and not paying complete attention to the task at hand). We used these directly as the probabilities of observing different attempt speeds when in different engagement states.

6.3.8 POMDP Policy Computation

We used an offline POMDP solver originally implemented by [109] and modified by [191] to solve for AT-POMDP's policy for help action selection. We computed AT-POMDP's belief update online and the robot's action selection based on our solved policy was determined in real-time during the repeated tutoring sessions with fourth grade students.

6.4 Evaluation

In this section, we evaluate our modeling approach by conducting a user study that explores the effects of an autonomous robot tutoring system that chooses help actions according to AT-POMDP's policy on student learning outcomes. We start by describing the educational context for the user study and the design of our integrated robot tutoring system, followed by our experimental conditions, procedure, and participants.

6.4.1 Evaluation Context

After discussions with a 4th grade teacher, we identified long division as a concept that students typically struggle with and would benefit from extra practice with in a robot tutoring scenario. Due to the complexity of long division and the wide range of abilities for students in fourth grade, we created two separate sets of problems representing two different difficulty groups in order to give each student problems that were at an appropriate level of challenge. We designed the math curricula for the tutoring sessions in line with common core standards for 4th grade students. The long division exercises that students completed were based on concepts they had at least been introduced to in their classrooms. Different students were at various knowledge levels on this particular topic. Based on conversations with 4th grade teachers, one aspect of long division that several students required help on was in utilizing the process of long division itself, as opposed to other strategies that may not scale to more difficult problems. For example, a student could successfully solve a problem such as 48 divided by 3 by drawing 48 dots and grouping these dots into groups of 3, but this strategy does not scale well to more complex problems such as 483 divided by 3. Students would benefit more from learning how to solve these problems using the strategy of long division. We focused our curriculum design on fostering improvement with both long division strategy use as well as successful application of division concepts (both using the correct strategy and obtaining a correct answer).

6.4.2 Robot Tutoring System

Our tutoring system consisted of a Nao robot and a tablet device for input and several software components that enabled the flow of an autonomous tutoring interaction. We used a ROS architecture to coordinate communication between the robot, tablet, and software components of the system that implemented our help action selection method [175]. The Nao robot acted as a tutoring agent throughout each interaction and facilitated the interaction by introducing each question, giving feedback on whether an entered answer was correct or incorrect, and proactively providing help according to which experimental condition the participant was in (described in Section 6.4.3). We designed our robot behavior and utterances to give the impression that the robot was providing the help to the student. Regardless of the condition the student was in, the robot displayed many behaviors to appear as a tutoring agent. For example, the robot waved and greeted students at the beginning of a session, shifted its direction of gaze to look towards the student at points during the interaction, and used gestures while talking.

The tablet application was used to display questions, feedback, and help to the students and was used as an input device for entering answers to each question. During a tutoring session, the tablet displayed each question one at a time, giving the student three potential attempts per question before moving on to the next one. For each incorrect attempt, the system would choose a help action, which would be displayed by the tablet and executed by the robot. After a third incorrect attempt, the correct answer would be displayed and

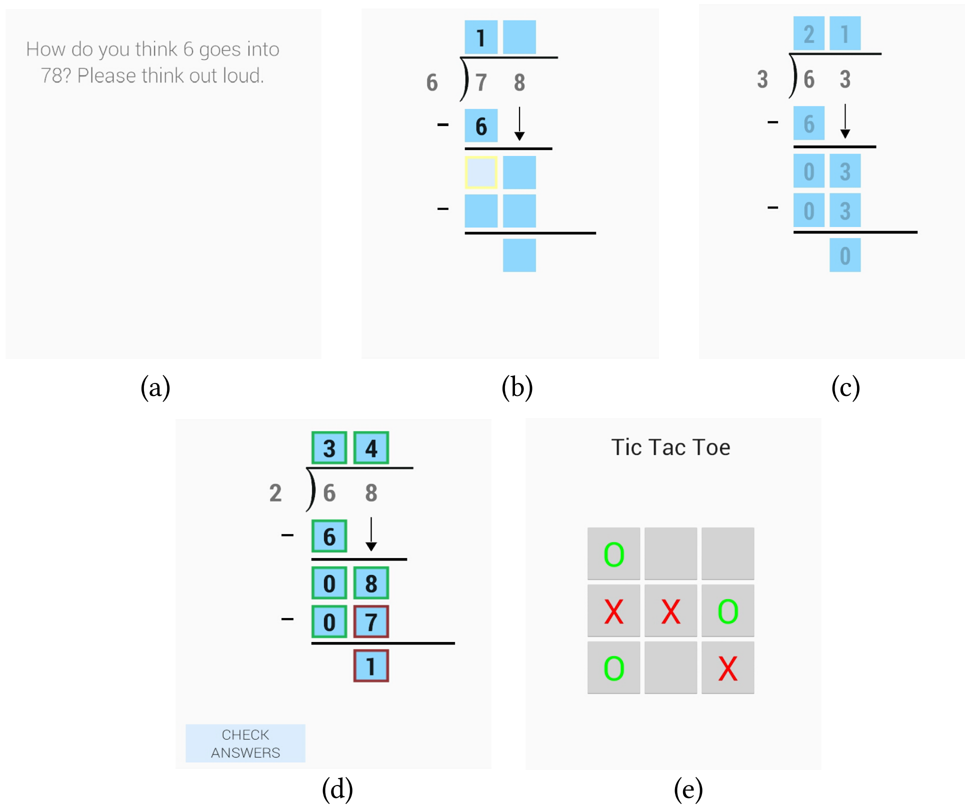

Figure 6.2: Screenshots of the tablet device displaying each help action used in the tutoring system setup. (a) *think-aloud*: the robot prompts the child to say the first step of the problem out loud. (b) *hint*: students receive the structure to the problem and can interact with the hint by filling in boxes. (c) *worked-example*: the robot walks the student through an example step-by-step. (d) *interactive-tutorial*: the student can interact with the tutorial and check their answers to intermediary steps of the problem to receive feedback. (e) *break*: students play tic-tac-toe with the robot for a non-task break during the tutoring interaction. Not pictured here is *no-action* in which students did not receive a help action and nothing was displayed on the tablet screen's help panel. While (a) shows an entire *think-aloud* prompt, (b) - (e) only capture a snapshot of the display rather than the entire help action.

students would move on to the next question. If a correct attempt was entered during the question, the student would receive feedback that their attempt was correct and would then move to the next exercise. Based on this design, students had two opportunities to receive help actions given by the system for each problem. The tablet had two panels, one in which the current question and input box was displayed, and the other in which interactive help would be displayed.

Based upon our discussions with a 4th grade teacher, we designed each of our help actions to be familiar to students based on what they had learned in class, and used the tablet device to display these interactive help actions. The students who participated in the study had been taught to use a "box structure" when they needed help with long division problems. We utilized this box structure in our implementation of several help actions, including hints, worked examples, and interactive tutorials. **Think-aloud** requests were made verbally by the robot and displayed in text on the tablet and did not involve the box structure as the robot asked the student to verbalize the first step in solving the problem. For the **hint**, the robot introduced the box structure displayed on the tablet for the problem they were currently working on, allowing students to interact with the box structure to help them solve the problem. **Worked examples** were provided in the help panel by showing a comparable problem to the current problem at hand. The robot verbally walked students through each worked example by filling in the boxes correctly one step at a time until all the boxes in the example problem were completed. The **interactive tutorial** involved displaying the box structure but only allowed the user to interact with the boxes associated with one "step" of the boxes at a time. Students were required to correctly enter the answers of the tutorial step and check their answers to the individual step to receive feedback from the robot before being able to move onto the next step. After a few incorrect attempts on a given step, the robot would fill in the boxes and move the student onto the next step. Students could also receive a non-task **break** during the tutoring interactions, and were given the opportunity to play tic-tac-toe with the robot. It was also possible for students to receive **no action**, if the system determined they did not need help on a given attempt. An example of each of the help actions displayed on the tablet can be seen in Figure 6.2.

6.4.3 Experimental Design

We designed a between-subjects study involving two experimental conditions—the *AT-POMDP* condition and the *fixed* condition. The purpose of comparing these two conditions is to understand whether the AT-POMDP policy for help action selection benefits students when compared to a "best practice" fixed policy for choosing help actions for students. All students received the same educational math content regardless of their experimental group. Students received help actions from the robot tutor based on the same criteria across groups, namely during each attempt made on a problem. Students in both groups also received actions from the same bank of helpful actions, which consisted of thinking aloud, hints, worked examples, interactive tutorials, breaks, and no action. What differed between the groups was the decision of which help action to provide to the student when help was being given. Below, we describe the action selection policies for each condition.

AT-POMDP Condition - The students in this group received help actions according to AT-POMDP's policy that we described in Section 6.3. AT-POMDP's policy chooses the best help action to give to the student based on its belief estimate of what knowledge and engagement state the student is in. AT-POMDP's belief state is updated after each observation is received and this is saved and loaded between each of the five sessions to preserve the model's state estimation over multiple sessions.

Fixed Condition - The students in the fixed condition received help according to a fixed policy we designed based on current practice in education and intelligent tutoring systems. Each time a student gets a question incorrect, they receive a help action, in order of the "smallest" help actions to the "largest" help actions. Considering the prior work on help provision in tutoring systems and the progressive nature of on-demand hints used in other tutoring systems, we created a fixed policy to provide progressive help in the following order: self-explanation request (*think-aloud*), hint about how to structure the problem (*hint*), a worked-out example that is explained step-by-step (*worked-example*), interactive tutorial involving back and forth with student participation and tutor feedback (*interactive-tutorial*). This mimics hint systems commonly used in ITSs where subsequent help given to students become more specific and helpful to solving the problem [5, 190]. This is also in line with a strategy commonly used by teachers when dealing with an entire classroom of students working. Because a teacher cannot provide more in-depth help such as a complex tutorial or a full worked example to individuals that may need help, they typically first provide a small hint, and then a progressively larger hint as they attend to the needs of the entire class. When a student answers a question correctly, the level of help provided resets to the smallest amount of help, which is a think-aloud. Students in the control condition received a break once per session, approximately halfway through the 15-minute session. This group serves as the control condition in our user study.

6.4.4 Experimental Procedure

Parental and child consent forms were collected for each student prior to participation in this experiment. Before interacting with the robot tutoring system, students completed a pretest that contained 8 questions that were designed to assess incoming knowledge about the division concepts covered during the tutoring sessions. Students were randomly assigned to one of the experimental conditions and then interacted with the robot tutoring system for five sessions, each lasting approximately 15 minutes. Each student completed as many problems as they could from a bank of practice problems designed for their assigned difficulty level within the 15-minute session. During each interaction, students sat at a table facing the robot and tablet and used scratch paper if needed. All one-on-one interactions were autonomous, requiring no input from the experimenter during tutoring. Each of the five sessions was completed on separate days and were spaced out over approximately three weeks. After all five tutoring sessions were completed, participants completed a posttest (on a separate day than their fifth session with the robot). The pretest and posttest were identical, each consisting of the same questions that encompassed relevant long division concepts that were represented during the tutoring interactions.

6.4.5 Participants

We recruited 30 participants from a local elementary school to participate in this study. Two participants were excluded in this data analysis (one due to non-compliance and one due to a perfect pretest score), resulting in a total of 28 participants. Participants were randomly distributed into the two experimental groups, resulting in 14 students per condition. The two groups were balanced based on gender, difficulty group, and approximate incoming knowledge level. Each of the two groups had exactly 6 males and 8 females as well as 7 participants in each of the two difficulty groups. The distribution of starting knowledge levels, determined based on pretest accuracy, was not significantly different between the AT-POMDP group (8 in K1, 4 in K2, 2 in K3) and the fixed group (7 in K1, 5 in K2, 2 in K3), $\chi^2(2, N = 28) = .178$, $p = .915$. All students in the study were in fourth grade, resulting in comparable ages between the AT-POMDP ($M = 9.29, SD = .47$) and fixed

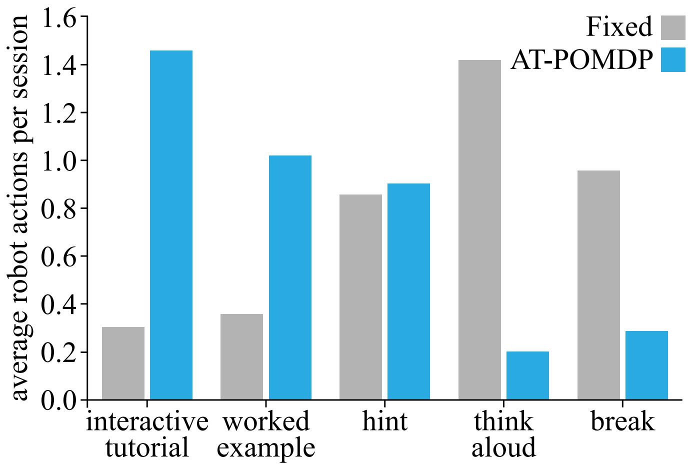

Figure 6.3: Average number of robot help actions received per session per student, highlighting the differences in actions selected between the AT-POMDP and fixed conditions.

$(M = 9.21, SD = .43)$ groups, $t(26) = -.422$, $p = .676$.

6.4.6 Results

In this section, we present findings characterizing participants' interactions with the system over the five tutoring sessions. We then present results on differences in learning outcomes for students between our two experimental groups. We also show metrics of how AT-POMDP's policy decisions differed from the fixed policy's decisions and highlight instances of participants who benefitted from the decisions of AT-POMDP's policy. When comparing our two experimental groups directly, we use independent t-tests and when assessing one group's progress by comparing within-subjects measures, we use paired t-tests. For all statistical tests, we used an α level of .05 for significance in our analysis.

Action Selection in Tutoring Sessions

Participants in both conditions received a similar number of help actions over all five sessions, where participants in the fixed condition received an average of 19.43 $(SD = 5.00)$ help actions and participants in the AT-POMDP condition received an average of 19.57 $(SD = 10.82)$ help actions, $t(26) = -.045, p = .965$. Since each session lasted only 15 minutes and many of the problems were challenging, participants each received relatively few help actions per session $(M = 3.90, SD = 1.65)$. Given the similarity of the two groups in terms of demographics and amount of help actions received during the sessions, the main differences between the two groups are the distribution of help actions selected by the AT-POMDP policy and the fixed policy.

Participants in the AT-POMDP and fixed conditions received a significantly different distribution of help actions across all five sessions, $\chi^2(5, N = 28) = 168.78, p < 0.001$, as shown in Figure 6.3. In addition to analyzing the difference in the actions chosen between the fixed and AT-POMDP conditions, we examined the differences in the actions chosen for participants in the AT-POMDP condition and the actions that would have been chosen for those same participants in the AT-POMDP condition if they had been in the fixed condition. We found a similar result in that the distribution of help actions across all five sessions was significantly different, $\chi^2(5, N = 14) = 98.23, p < 0.001$. Additionally, 85.4% of the 274 total actions the participants in the AT-POMDP condition received were different than the actions they would have received had they been in the fixed condition. These results support the conclusion that participants in the AT-POMDP and fixed conditions received significantly different distributions of help actions and, additionally, that the actions chosen by the AT-POMDP and fixed action selection policies were also significantly different.

Learning Gains

Students completed a pretest before the first tutoring session and a posttest days after the fifth session. Each student received a test score for both the pretest and posttest that were each scored between 0 and 1. Students were awarded one point for each question they used the correct strategy on as well as one point for every question they answered correctly. This scoring scheme was in line with the design of our mathematical content, awarding points for both accuracy and correct strategy use. Below we define normalized learning gain to measure improvement from pretest to posttest for each student i:

$$nlg(i) = \frac{score_{\text{post}}(i) - score_{\text{pre}}(i)}{1 - score_{\text{pre}}(i)} \tag{6.2}$$

These scores were calculated by diving the number of points received by the total number of points it was possible to receive for each test. The metric of nlg provides a measurement of

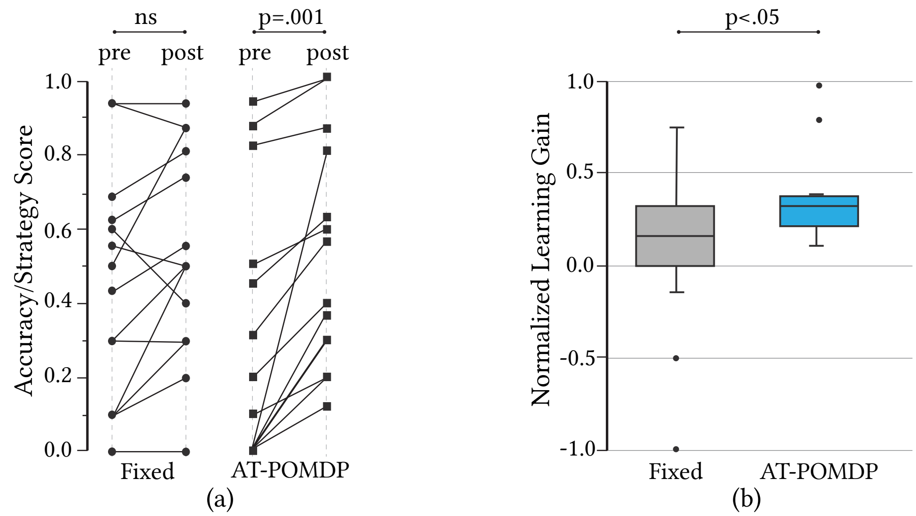

Figure 6.4: Learning gains results demonstrate the effectiveness of AT-POMDP's policy in providing help. (a) Students who were in the AT-POMDP group significantly improved their test scores from pretest to posttest. (b) Students who were in the AT-POMDP group improved their scores based on accuracy and strategy use significantly more than those in the fixed group.

learning improvement for each student, accounting for different starting knowledge levels.

There was no significant difference between the pretest scores for the fixed ($M = .44, SD = .31$) and AT-POMDP ($M = .30, SD = .36$) groups, $t(26) = 1.146$, $p = .262$. For students in the fixed group, posttest ($M = .54, SD = .28$) scores did not differ significantly from pretest scores ($M = .44, SD = .31$), $t(13) = -2.128$, $p = .053$. Students in the AT-POMDP group had posttest scores ($M = .53, SD = .30$) that were significantly higher than their pretest scores ($M = .30, SD = .36$), $t(13) = -4.473$, $p = .001$. In comparing normalized learning gain between the two groups, we found that average nlg for the AT-POMDP group ($M = .41, SD = .30$) was significantly higher than for the fixed group ($M = .08, SD = .43$), $t(26) = -2.326$, $p = .028$ (Figure 6.4). These results indicate that the students who received help actions from the robot according to AT-POMDP 's policy improved their strategy use and accuracy on long division concepts significantly more than the students who received help actions according to a fixed policy. Given that students across groups only received approximately 4 help actions per session on average, it is somewhat surprising that we saw differences in learning gains between the two groups. This highlights the importance of each decision of what help action to provide over the course of the tutoring sessions.

Case Studies

In this section we take a more in-depth look at three individual students in the AT-POMDP condition. For these students, we examine the tutoring action choices made by AT-POMDP's policy and evaluate the effectiveness of these choices.

Participant 11 (P11) was one of the highest performing students in our sample. P11 not only answered more attempts correctly on average per session (92.1%) as compared with the entire cohort of students (41.2%), but also completed more problems on average per session (21.4) as compared with the entire cohort of students (5.2). Of the 114 attempts P11 made on problems over the 5 sessions, P11 received 7 tutoring help actions from the robot, selected by the AT-POMDP policy: 1 *hint* (session 1), 1 *break*, 1 *think-aloud*, and 4 *no-actions*. Given that P11 displayed a high mastery of the long-division material, AT-POMDP estimated that P11 was in a high knowledge state and thus, the cost of selecting help actions like hints, worked-examples, and interactive-tutorials would have been too high to be worthwhile, so the model selected a majority of no-action help actions for P11. Despite not receiving help when AT-POMDP selected *no-action*, P11 answered the next attempt correctly 3 out of the 4 times this occurred.

Participant 25 (P25) was one of the lower performing students in our sample. P25's accuracy on the attempts (19.1%) was lower than the sample's attempt accuracy (41.2%). Additionally, P25 answered merely 1.8 attempts correctly out of 9.4 on average per session. Of the 25 help actions AT-POMDP's policy selected for P25, 12 were *interactive-tutorials* and 7 were *worked-examples*, the two most comprehensive and involved tutoring help actions. P25 did not answer any questions correctly on either the pretest or the posttest, however, attempted 2 (out of 5) more long division problems on the posttest than the pretest, showing an increased confidence with attempting long division problems. Had P25 been in the fixed condition, the fixed policy would have selected 9 *think-alouds* and 8 *hints*, the two most minimal tutoring help actions, and only 4 *worked-examples* and 3 *interactive-tutorials*. It seems unlikely that if P25 had been in the fixed condition, P25 would have grown in confidence and familiarity with long division from the pretest to posttest since

P25 would have received considerably less long division assistance as compared with the help P25 received in the AT-POMDP condition.

Participant 12 (P12) was also one of the lower performing students in our sample. P12's accuracy on question attempts (9.8%) was substantially lower than the entire sample's attempt accuracy (41.2%). P12 answered a meager 0.8 attempts correctly out of 8.2 attempts on average per session. From watching P12's tutoring session videos, P12 was a student that tended to be more distracted and disengaged than the average student, likely due to the difficulty of the problems and P12's low attempt accuracy. The AT-POMDP policy selected a total of 5 tic-tac-toe *breaks* across the 5 sessions: 1 break in sessions 2, 3, and 4, and 2 breaks in session 5. P12 received all of these breaks after an incorrect answer on the previous question with a faster speed ($M = 27.2s, SD = 9.0s$) than P12's average question answering speed ($M = 67.6s, SD = 43.5s$), indicating that P12 was presumably making blind guesses and that a break would likely be useful for re-engaging P12. After the tic-tac-toe breaks, P12's accuracy on the next attempt was 40.0%, much higher than P12's overall attempt accuracy during all of the sessions, 9.8%, suggesting that the breaks were well-timed and effective for P12.

Through the examination of these case studies, we encounter three diverse action selection approaches by the AT-POMDP policy: giving limited help to a student who displayed mastery of the material, providing significant help to a student who showed little mastery of long division, and administering appropriately timed breaks to a student who was frequently disengaged. In all of these cases, AT-POMDP's policy exhibited successful and effective action choices, supporting the learning and engagement of the students.

6.5 Discussion

In this work, we built a model that enabled robot tutors to autonomously select help actions based on an estimate of their knowledge and engagement levels. We demonstrated that with a single, unified model, we could provide different help actions to individual students according to their needs. By evaluating the effectiveness of AT-POMDP in a five-session long-term tutoring interaction, we demonstrated that students strengthened their learning on a long division task by exhibiting improved test scores based on accuracy and correct strategy use. Furthermore, these students improved more than students who received help from the robot tutoring system according to a fixed policy. Our results highlight the value of building robust, computational frameworks to deliver personalized tutoring support over time for young students.

As human tutors are highly capable of providing different types of help to students exhibiting different skill proficiency levels, we wanted to emulate that type of flexibility with AT-POMDP for help action selection. By examining certain participants in closer detail, rather than just looking at the average learning gains for each group as a whole, we can see specific instances in which AT-POMDP's policy selected appropriate actions for the individual child. Because it was one model that provided vastly different actions in accordance with each individual student's state, we note that this level of personalization is an important component of our model and validates its flexibility in practice. Other investigations into probabilistic models for planning tutorial actions have also demonstrated the benefits of this type of approach that can plan under uncertainty in finding useful policies for teaching tasks [161, 176]. Our work is in agreement with this body of work, and we provide further evidence for the usefulness of a POMDP model used to plan under uncertainty in a long-term tutoring setting for children. Rather than focus on the sequencing of teaching content, we plan supportive help actions the tutor can take to foster efficient learning and strengthen student learning of a concept that is challenging for them.

Our results indicated a difference in average learning gains between the AT-POMDP condition and the fixed condition. However, the AT-POMDP condition differed from the fixed condition in a number of ways. There were several factors that could have led to this observed difference in performance improvements between the conditions. The distribution of help actions was significantly different between our conditions, making it possible that actions sampled from AT-POMDP's resulting action distribution but not selected by AT-POMDP's policy could lead to the same results. In addition, AT-POMDP on average selected more worked examples than the fixed policy selected, which may have contributed to some of the improved performance of the AT-POMDP condition given that other work in tutoring systems have found worked examples to be effective [156, 185]. As the fixed policy provided help in the same order after each incorrect attempt, another difference is the variation in the order of help actions received by the AT-POMDP condition. AT-POMDP also specifically models student knowledge and engagement states, however it is not clear whether the explicit modeling of each of these types of states individually contributed to the performance gains made by the AT-POMDP group. While we demonstrated that AT-POMDP's policy could be used for personalized help action selection in tutoring, additional research and user studies must be conducted to tease apart exactly which factors led to the difference in learning gains between conditions and to what degree each factor influenced the results.

Though our model's policy for selecting help actions for students was effective in strengthening learning outcomes, we found that not all students improved their long division skills. After discussions with one of the 4th-grade teachers at the public school where the user study was deployed, we began to understand the variance between students in skill competencies on a concept as complex as long division. We found that the students who made larger improvements were typically already performing at an intermediate level. The lowest performing students often received "larger" help actions frequently, and this may have helped them improve their attempt rate as well as their tendencies to employ the correct strategy when solving long division problems. However, we noticed that those who started with extremely low incoming pretest scores, were typically unable to demonstrate strong mastery of complex long division skills even after five sessions. We acknowledge that our model could still benefit from additional personalization, such as adapting the help action choice according to individual preferences.

Another limitation that affected the quality of AT-POMDP's decisions to take a given action in a certain context has to do with our observation space. Utilizing a student's incorrect and correct attempts as observations that correspond to an estimate of knowledge level is common in intelligent tutoring systems. Though we found that timing or efficiency in completing problems may be a good determinant of when a student needs a break in Chapter 3, here we used timing as part of our observation as an estimate of whether the student was engaged or disengaged. Exploring more elaborated estimations of this user state may lead to better planning for when a student is disengaged, such as using head pose data or EEG data [140, 216]. Nonetheless, even state-of-the-art computer vision techniques cannot perform this sort of detection well, making our timing mechanisms a practical proxy for engagement that can be used in our real-time, autonomous tutoring system.

The user studies described in Chapters 3 to 5 each focus on salient aspects of tutoring interactions for children and describe methods to provide different types of support to students. In this chapter, we wanted to employ the design guidelines and lessons we had learned about building autonomous robot tutoring systems for children into the creation of our help action planning model, AT-POMDP. We incorporate both breaks (Chapter 3) and metacognitive strategy assistance (Chapter 4) as supportive actions that the robot tutor can take, and provide proactive assistance to the student, bypassing the problematic choice of students dealing with on-demand help features (Chapter 5). We designed and selected AT-POMDP's parameters based on empirical data we collected from our user study on shaping productive help-seeking behavior (Chapter 5), and built a flexible model that can handle a variety of different scenarios for children of different capabilities. The work conducted in this chapter underscores the main theme that runs throughout this dissertation: carefully designed personalized robot tutoring systems can enhance learning outcomes for children.

6.6 Summary

In this chapter, we built a state-of-the-art computational model (AT-POMDP) to provide personalized support to students practicing a difficult math concept over several tutoring sessions. We employed a POMDP approach to estimate a student's individual knowledge level and engagement level and provide decisions on the appropriate help action to take to increase likelihood of the student reaching higher knowledge levels. Our model was effective in providing a personalized approach to planning and balancing several different help actions in a tutoring setting. Our evaluation demonstrated the effectiveness of using AT-POMDP to help students with a long division math task as students receiving help from AT-POMDP's policy improved their learning gains as compared to students receiving help from the fixed policy.

Though students generally demonstrated some improvement regardless of their experimental group, the benefits of the model on student learning were apparent. In our analysis, we saw that there were no differences on average between students in each of the two groups, and that they received relatively few help actions on average due to the total number of problems students completed on average (they were generally challenging for most students). Still, with the small number of action decisions that differed between the two groups, it was the students in the AT-POMDP group who improved their test scores from pretest to posttest, indicating the importance of these decisions the robot tutor made over the course of the five sessions.

One of the main contributions of this model was its flexibility. We chose particular actions for our model that we thought would be useful during tutoring based on prior work in intelligent tutoring systems as well as our own prior user studies investigating the usefulness of particular support behaviors for robot tutors. AT-POMDP could be extended to provide other types of supportive actions, as well as explore the benefits of using other types of observations that may be more informative than just attempt accuracy and attempt timing in estimating knowledge and engagement level. Even though we conducted our long-term user study evaluation with fourth grade students practicing long division concepts, this model for planning help actions could be readily applied to a variety of other tutoring scenarios and populations.

The other important contribution of both this model and empirical evaluation is the personalized support it provided to individual students during a challenging math task over multiple sessions. One of the common themes we see throughout the studies in this dissertation centers on the vast individual differences between students of different skill levels and abilities. Having a single computational model that can dictate when to provide a tutorial to a stuggling student, give a break to a disengaged student, and withhold help to a very advanced student exhibits the power to handle these individual differences in a way that addresses the needs of each student. As this type of personalization is often cited as the reason that human tutors are so successful, this is an important step towards building effective robot tutors that can truly enhance learning for students in today's schools. In the next chapter, we further expand on common themes throughout this dissertation and ground our findings from the last several chapters in relation to challenges that still exist in the field of robot tutoring systems.

Chapter 7

Discussion

In this dissertation, we describe a body of work that seeks to understand how we can build effective robot tutoring agents to enhance learning for children. We conducted four user studies exploring several salient aspects of tutoring interactions, each involving children interacting with an autonomous tutoring system in a real-world educational context. We also described an architecture that can be used to inform the design of robot intervention behavior and developed a computational model that provides different help actions to students in a personalized way. All of the work conducted in Chapters 3 through 6 also contributes to a broader understanding of the importance of personalization in learning. In this chapter, we present design guidelines for building robot tutoring interactions for children, highlight important themes in our work, and present open questions and challenges that should be explored by future work.

7.1 Design Guidelines for Effective Robot Tutoring Systems

The user studies conducted in this dissertation give rise to several evidence-based design guidelines for building effective robot tutors for children. We list them below:

- Breaks are a useful mechanism to sustain engagement during a cognitively taxing tutoring interaction. Rather than the number of breaks, it is the timing of these breaks that can restore student performance.

- Students struggle with using metacognitive strategies during complex problem-solving, but using a robot tutor to provide close, responsive support can help them utilize these strategies.

- Children do not utilize the help features in a tutoring environment in an ideal way on their own. Robot tutors can be used to regulate access to the help in order to shape more productive behavior in a tutoring environment.

- Individual differences ranging from incoming knowledge level to attention span during tutoring are prevalent in children; it is important to analyze performance gains relative to individual baselines rather than just look at averages at the group level.

- Though it is challenging to robustly sense the learner, using reliable measures of performance such as accuracy and efficiency can be informative in monitoring more complex user states over time.

- Due to the novelty of robots, children typically rate robots on subjective scales extremely highly, even prior to any interaction. It is difficult to measure changes in perception over time due to this high initial rating, which produces a ceiling effect. To assess the effectiveness of a tutoring system for children, it is more reliable to use objective measures of student behavior and learning progress than to use subjective measures of children's perceptions.

- Curricula for tutoring systems should be carefully designed so that the difficulty of the exercises or content matches the level of the students the system is deisgned for. Validating the difficulty of the content with a teacher familiar with the target domain and age group of the students is beneficial.

7.2 Themes

This dissertation seeks to understand several salient aspects of successful learning within robot tutoring interactions. In Chapters 3 through 6, we conducted several rigorous, well-controlled user studies showing that personalized behavior in robot tutors can enhance learning gains for students. We also presented two more general architectures for designing robot behavior: one that provides an intuitive way to design robot intervention behaviors based on user behavior (Chapter 5), and one that autonomously provides help actions to students based on their knowledge and engagement levels (Chapter 6). Our pursuit in researching robot tutors centers on understanding what behaviors social robot tutors can employ to positively impact learning outcomes for children. Below, we discuss several important themes and contributions that span all of the research described in the previous chapters.

7.2.1 Flexibility of Frameworks for Robot Behavior

Aside from the findings of our user studies, the main contributions of this dissertation are two frameworks for designing effective robot behavior, which we describe in Chapters 5 and 6. Though we validated each of these with user studies involving children interacting with a robot tutor in the context of a math task, the frameworks themselves are not inherently specific to the robot platform we used, the curriculum we developed, the population we targeted, or the parameters we chose which were derived based on the particular problem we were investigating. Both frameworks can be adapted to work in other application domains, and can be useful in the design of effective robot behaviors in novel settings such as helping adults practice for a standardized exam [48], teaching young children about healthy food choices [209] and fostering sign language learning for deaf infants [203]. For our framework described in Chapter 5, we chose parameters based on user behavior within our specific system; however, these parameters could be changed in a different learning scenario to examine user behavior and derive intervention behaviors accordingly. Moreover, for the computational model described in Chapter 6, though we derived specific parameters from prior data we collected, these could be altered based on new data, domain knowledge, or expert input and readily used for providing other types of support in a variety of educational contexts. An important aspect to the work conducted in this dissertation is the open and extensible nature of the frameworks we outlined for designing robot behavior in tutoring settings for children.

7.2.2 Importance of Personalization

The work done in this dissertation specifically highlights the importance of personalization in the design of robot behaviors for effective tutoring interactions. For example, personalizing the timing of when to provide a break during a cognitively taxing interaction according to changes in the student's behavior relative to their own baseline led to increased learning gains (Chapter 3). As we moved towards more robust computational models that could plan what help actions to provide to a student over multiple tutoring interactions, we saw that planning these actions based on an estimate of the student's knowledge and engagement levels also positively impacted learning in children (Chapter 6).

In the field of Human-Robot Interaction (HRI), it is often a common belief that the more social behavior or personalization a robot employs, the better the interaction. Work in robot tutoring has often drawn similar conclusions by investigating social robots that employ emotional support, a robot tutor employing more immediate non-verbal behaviors, and robots utilizing multiple types of social support including attention-guiding and communicativeness [115, 136, 200]. However, an important body of work by Kennedy et al. found that just increasing the amount of social behavior employed by a robot tutor does not necessarily lead to learning gains and that "too much" social behavior could be potentially distracting to students [114]. This indicates that just adding more social behavior does not mean that a student will learn more or perform better. Rather, the personalization and behavior that the robot tutor employs must be designed carefully to address an important aspect of the tutoring interaction in order to potentially impact learning outcomes.

This is the point we illustrate in Chapter 5, showing that even simple intervention strategies can be effective in promoting learning if the strategies are targeting behaviors that relate to important user attributes such as self-regulation. Each of the findings from our work demonstrate that the personalization of key aspects of tutoring systems can enhance learning for children: (1) breaks provided on a personalized schedule to user performance can be used to sustain engagement; (2) close, personalized support can be used to help children successfully use a metacognitive strategy; (3) personalized intervention behaviors can be used to shape more productive help-seeking behavior over multiple tutoring sessions; (4)

continually updating a belief of the individual student's knowledge and engagement levels can be used to provide personalized help effectively to students with varying abilities. The work conducted in this dissertation contributes to the growing body of research bolstering the importance of personalization in building effective robot tutoring interactions for children.

7.2.3 Measurements of Learning Outcomes

Learning is an extremely complex process that is highly individualized and is notoriously difficult to measure [164, 214]. Schools typically use grades and test scores to understand the performance of their students over long periods of time, such as a semester that lasts several months [228]. Typically when evaluating the effectiveness of a teaching strategy or use of a novel teaching method, students can be evaluated relative to their own individual performance baseline from before the intervention to after the intervention is complete, by employing a difference score that captures the change between pretest score and posttest score. Then the difference score can be normalized by the amount of potential improvement the student had to gain, which is done to account for students starting out at different incoming knowledge levels. Each of our user studies relied on using a pretest/posttest measure [65], calculating the normalized difference in individual scores between these two tests relative the starting score, and comparing the difference in normalized learning gains between experimenal groups. This is a valid way to assess student learning improvement, as it allows us to be confident that we are measuring the impact of the particular robot tutoring system against a control condition, accounting for differences in incoming ability. Most of the other robot tutoring systems that have demonstrated usefulness in a variety of tutoring tasks and domains have followed a similar approach [116, 142, 206]. This allows us to understand whether each of our behavioral mechanisms is impactful at a higher level of analysis.

We have also tried to examine user progress on a more fine grained time-scale, such as using changes in performance during the actual tutoring sessions to understand the impact of some aspect of the robot tutor. For example, we looked at local improvements of efficiency and accuracy in our user study on providing breaks during tutoring (Chapter 3).

Additionally, we measured immediate responses to a robot tutor's supportive prompting to assess student engagement and compliance in their use of a metacognitive strategy (Chapter 4). In our computational model that relied on real-time observations of user performance, we used participants' accuracies on each question as well as relative timing changes to inform the model's belief state of the user's knowledge and engagement levels. Though the pretest/posttest normalized learning gain metric represents overall improvement as a result of the intervention, it does not always capture smaller improvements in performance and understanding for each student. These smaller changes can also differ greatly between students: one student who may take longer on a problem may be disengaged and for another, this may mean they are thinking deeply and this may be beneficial for their learning. The contextual nature of these short-term measures of learning and performance make it difficult to draw conclusions across diverse students. Furthermore, learning progress is not always steadily increasing for different students, and a student demonstrating wrong answers does not necessarily indicate no improvement is being made. This makes it challenging to measure and interpret short-term learning gains during a tutoring session.

However, students at a very low incoming knowledge level who struggle with learning often make no measurable gains from pretest to posttest, but occassionally demonstrate smaller improvements during the tutoring interactions with the support provided. We saw this occur for a handful of students in the four user studies we conducted (individuals who started with low pretest scores and ended with low posttest scores can be seen in Figures 3.5, 4.4, 5.5, and 6.4, where individual test score improvements are pictured). Because of this, it is important to also consider smaller, more transient measures of improvement during learning even though they are less well understood due to their difficulty to measure. It also indicates that the importance of a highly personalized tutoring system: finding additional personalization strategies to handle more extreme measures of performance during learning is still an open challenge that would benefit from further research.

7.2.4 Robot Tutoring "in the Wild"

As HRI has been an emerging field over the last decade, investigating social robots as tutors is a relatively new area of research. HRI experiments often generate empirically-demonstrated findings, as research questions are typically investigated through a user study or controlled observation of humans interacting with robots. However, many of these studies often involve adult participants that do not necessarily represent the true target population for the system, and laboratory contexts that are created or manufactured specifically for a particular study or investigation [142, 206]. Some other studies in robot tutoring have strived to conduct investigations in the context of authentic, "in the wild" tutoring settings for children [87, 116, 136]. In line with these influential studies, one of the main themes in our work is the emphasis on conducting robust, real-world studies involving authentic educational concepts for children in public school classrooms. In each of the user studies described in Chapters 3 to 6, we designed educational content to match what students were learning in schools and often talked to teachers who had experience with students of our target age in order to ensure the appropriateness of the exercises that students completed. In addition, instead of bringing adults or even children to a lab setting where we could control more of the environment, all of the evaluations of our robot tutoring systems involved conducting a user study with children in local public schools. Finally, rather than just investigate behavior mechanisms that may impact learning in a single session, we validated our two frameworks for building effective robot behaviors in longer-term studies involving multiple tutoring sessions spread out over a few weeks. Conducting multi-session studies in the wild is considerably more challenging than a study that only spans a single session. This is due in part to the additional time and resources required by the experimenters and the children at schools, but mainly centers on the idea that dynamic behavior is necessary to keep children engaged over several different tutoring sessions once the original novelty of interacting with the robot tutor wears off. Validating our architectures in the context of longer-term user studies with children in schools greatly strengthens our results and findings and is one of our main contributions to the advancement of effective robot tutoring systems.

7.2.5 Feasibility of Building Autonomous Systems

Another common theme throughout all of the work conducted in this dissertation is the focus on building autonomous systems with the current technology we have available that works in real-world settings. In our general robot tutoring system setup, we always used a tablet device to circumvent the problem of detecting what the student was doing in real-time. In Chapter 3, we explored providing breaks to students to sustain engagement over time. However, we were limited to detecting engagement via a proxy measure that we knew we could detect robustly, namely time to complete exercises. We also built an autonomous system capable of supporting students in using a metacognitive strategy while completing complex math problems. In Chapter 4, we used open-source software that could detect whether the student was talking or not talking [74], and used this to decide when the robot would prompt students to continue talking out loud. In Chapter 5, we studied the help-seeking behavior of students interacting with a robot tutor, by allowing them to request help from the robot by pressing buttons visible on the tutoring application displayed on the tablet screen. The decisions to build tutoring systems that could operate autonomously rather than use more advanced technology (for example, parsing child speech which is extremely challenging [118]) that did not work as well was due to our committment to deploy systems that did not involve human intervention into schools to conduct our user studies, and to build systems that worked robustly over multiple sessions in a dynamic environment. We focused on building these systems to investigate the answers to our research questions using today's technology with real students in authentic settings, allowing us to draw conclusions from our results that are readily applicable to deploying robot tutors in schools.

Our systems provided a practical implementation of robust robot tutoring systems that could impact learning gains in the tutoring scenarios we designed. As technology improves and robot sensing capabilities become more advanced, the feasibility of building more complex systems that can more efficiently detect salient aspects of learning must be explored. Some examples of advanced sensing that would likely benefit the advancement of autonomous tutoring systems include robust detection of boredom, confusion, and frustation. These learning-centric affective states are important indicators of performance in a tutoring scenario and tutoring systems that can intelligently monitor and respond to these states are likely to improve their overall effectiveness. As engagement is also a fundamental factor in learning, a sensing system that could detect disengagement in real-time, independent of the educational context would be useful. This is currently challenging as engagement often looks different for individual students and can depend on the task at hand. Finally, robot tutoring systems that can more rigorously measure and detect motivational attributes such as self-regulation, self-efficacy, and academic confidence will be crucial in designing the next generation of systems that help students become more effective learners.

7.3 Open Questions and Future Directions

In this section, we discuss several open challenges and future directions that must be explored in robot-child tutoring in order for this field to be truly applicable in the educational domain and impact student learning on a much larger scale. While we have examined some of these questions and other work in HRI has also investigated various facets of these issues, most of them have not been explored to the fullest extent. We discuss the following issues that will continue to influence the state of robot-child tutoring interactions as the field grows: the role of embodiment, leveraging affect, building adaptive systems, supporting student self-efficacy and metacognition, and impacting education at scale.

7.3.1 Role of Embodiment and Social Behavior in Tutoring

A large body of work has investigated the advantages of physically present agents, over virtual counterparts or non-embodied agents [112, 119, 143, 144, 173, 227]. For example, robots have been shown to foster increased enjoyment and compliance in adults compared to on-screen agents [18, 168]. Our work in this dissertation did not focus on proving the efficacy of physical robot tutors, but rather built on the work of others indicating the value of physical robot tutors due to their ability to foster cognitive learning gains in adults [143]. In Chapter 4, we did compare a physically embodied tutoring system that provided metacognitive strategy support to a tutoring system that contained the same supportive behaviors from a non-embodied tutor voice, and found that students engaged and complied with the support more if the support was delivered by the robot, providing further evidence for the value of physically-present robot tutors. Still, much of the work we conducted was focused on demonstrating the effectiveness of personalized behaviors for the robot tutors to impact learning gains, and could be applied to other intelligent tutoring systems as well. However, given that virtual agents can also be social tutoring agents and are not limited by the challenges of deploying physical systems, it is important to consider exactly when physically present robot tutors are necessary [34].

Though physically-present robots have shown to hold promise as effective tutors, we still do not know exactly why this is the case or what about robots causes this phenomenon. After the seminal work of Leyzberg et al. demonstrating that the physical presence of robot tutors increases cognitive learning gains in a puzzle solving task with adults [143], other research investigated the role of embodiment and social presence in educational scenarios. Though learning gains did not differ with children completing a conceptual learning task with a physically present robot versus an on-screen version of the same social robot exhibiting the same social behaviors, the physical robot corresponded to increased social presence, which may be beneficial for learning in certain circumstances [112]. Other work has also focused on user perceptions of physical robots versus animated agents, specifically showing that users perceive physical robots as more credible, engaging, and informative [119]. Based on these findings, it is likely that the physical nature of a robot tutor itself does not automatically "cause" learning gains in students, but rather is a consequence of the other social behaviors that arise when interacting with a physical robot tutor (such as engagement and compliance), which may be due to the social presence and embodiment of a physical robot tutor. Future work should still focus on teasing apart what properties of robot tutors are critical for learning and what role the social presence and behavior of the robot contributes as compared to the physical embodiment itself.

7.3.2 Affect in Robot Tutoring

Human tutors are often thought to be highly successful due to their ability to simultaneously manage cognitive and affective signals from students [141]. Our work has utilized reliably detectable features to assess user attributes like timing for engagement (Chapter 3, 6) and hint requests that relate to measures of motivation in learning (Chapter 5). In order to reach their full potential, social robots may be able to further enhance learning by detecting more complex user states reliably and then acting accordingly. Directly sensing measures of motivation, attention, and engagement might improve our existing systems that rely on indirect measures such as time to complete problems. Currently, more complex user attributes and states are extremely challenging to detect via computer vision as they are typically constructs that are not directly observable (i.e., motivation, personality, preferences, etc.)

Some work in tutoring systems has explored sensing affect and attention for robot tutoring systems [27, 139, 140, 216]. For example, head pose has been found to be an inadequate proxy for gaze [113] and may not necessarily be a good indicator of attention in certain tutoring tasks as some students tend to turn their head in different directions while thinking. On the other hand, eye gaze was found to be a useful channel of information for children in a learning task and could be explored further [27]. Furthermore, some work has explored building classifiers to detect disengagement and has found that the features important in this detection differs for one-on-one interactions and group interactions [139]. Szafir et al. successfully used a low-cost EEG sensor to track attention in real-time, allowing a robot to intervene when attention dropped [216]. Other systems are beginning to leverage sensors that do real-time facial recognition and provide estimates of complex user states, such as engagement and valence based on facial expressions and other facial features such as eyebrow raises [87, 152]. Many teaching systems are also detecting non-verbal cues such as gestures and posture that may signify a change in attentional state [27, 201]. Though most robot tutoring systems do not rely on natural language processing due to the difficulties in parsing child speech [118], certain intelligent tutoring systems have explored dialogue systems in tutoring scenarios [90, 91]. Some applications have made strides toward being able to use verbal cues, such as prosody, in robot interactions with children [198]. As speech systems become more robust, especially for children, robot tutors may be able to explore communicating with users through natural language dialogue, and using the content of a user's speech to more accurately assess a student's knowledge level.

Some of the most challenging states to detect in a learning setting involve attributes related to motivation, as well as learning-centric affective states such as boredom, confusion, and frustration [67]. Work in the ITS community has attempted to build detectors for these types of states using features such as keystroke analysis, logfile data, and conversational cues from written dialogue [35, 52, 68]. Efforts to detect user affect have also investigated using sensors like cameras, pressure sensing chairs, and devices that measure skin conductance to detect important user features such as facial expressions and posture patterns. [66, 111]. Because of the complexity of these affective states, they often cannot be detected in the same way for different students and do not transfer well in different application contexts. Exploring more generalizable detectors of these crucial affective states should be a focus of sensing systems for robot tutors, as being able to intelligently respond to these states during a learning interaction will likely lead to more effective tutoring interactions. As the quality of computer vision systems gets better and other sensors become more cost effective, robot tutors must continue to investigate how they can more reliably detect measures of attention and other affective user states in diverse learning environments and utilize this information in their behavioral models to further enhance learning.

7.3.3 Adaptive Robot-Child Tutoring

In order for intelligent robot tutors to foster learning over much longer periods of time in real-world environments such as classrooms and homes, they must learn to adapt based on the individual. Our level of personalization in our autonomous robot tutoring systems typically involved producing robot behaviors in response to certain criteria that was specific to the individual. In Chapter 6, we built a model that is more personalized than our previous systems, as it maintains a belief state of an individual's knowledge and engagement levels and provides help accordingly. In order to better handle individual differences in the long-term, these behavior mechanisms must be able to adapt to the needs of the individual student over time as well as be able to handle whether certain behaviors and strategies work differently for some students. This requires receiving some sort of feedback from the system to understand what is "working" for a given student. For example, a natural extension to the model we described in Chapter 6 for providing help actions to students practicing a challenging math concept would be to evaluate whether certain students responded more favorably to specific help actions. The system could make use of this kind of information over time rather than assume each help action generally works in the same way for all students. Reinforcement learning or other computational methods that can make use of positive or negative rewards should be explored as a framework for building truly adaptive tutoring systems for long-term interactions. While promising, this is a large challenge for the field as these methods typically require a large amount of training data, which is often difficult to receive in real-world tutoring scenarios. Nonetheless, methods that can give robot tutors the abilities to adapt to the user over the long-term must be a central focus of research in robot-child tutoring. As commercial robots become more common in classrooms and households, advances in cloud robotics may provide a way to more feasibly collect large amounts of data involving children in learning scenarios [101]. This would enable the collection of data from many children in order to train models, as well as leverage interaction experience across users instead of only utilizing data and experience from a single robot interacting with a particular individual. While this may improve robot behavior models for long-term interactions, educational data and information about students can be considered sensitive, indicating that privacy and data storage may be potential challenges to consider in using cloud robotics in education.

7.3.4 Evaluating Robust Learning: "Learning to Learn"

We are the first to explore direct metacognitive strategy use specifically in robot tutoring for children, by exploring both use of the think-aloud strategy in problem solving (Chapter 4) as well as shaping productive help-seeking behavior as a means to enhance learning (Chapter 5). One other body of work done by Jones et al. has looked into robot tutors using open-learner models to increase self-regulated learning skills in children [107, 108]. Other work involving robots teaching other non-traditional skills such as anti-bullying behavior has also shown to be a promising area for robots in education [138]. In order for children to become productive, independent learners, it is important for them to learn skills which increase their self-efficacy and academic independence. There is a large area to explore in understanding how robots can foster more robust learning skills, by exploring if they can effectively teach students self-regulation skills and metacognitive strategies and support them in their use. Human teachers are highly skilled at motivating young students and allowing them to solve problems with a sense of independence [141]. Because many of these skills are social in nature, social robots, with their embodied presence and capabilities for social interaction, are well-suited to enhance these types of skills in students. Social robots, which have been successfully used to motivate older adults to exercise [75], provide empathic support for children [136], and encourage social interaction skills for children with autism [121, 188], must leverage their social interaction capabilities to focus on enhancing self-efficacy and self-regulation skills in learners. This has the potential to transform learning in a larger way, as these skills are crucial for academic and professional success in the long-term and provide a unique area for social robot tutors to demonstrate their effectiveness.

7.3.5 Robot Tutors as Real-World Systems

In order for robot tutoring systems to become a feasible educational technology that can impact learning for students at a much larger scale, several limitations of current state-of-the-art tutoring systems must be overcome. Even for studies handling longer-term educational interactions, these are typically on the order of under ten sessions and these sessions are stand-alone sessions in which students interact with the system for each session generally for a shorter period of time (typically under one hour). If we want to utilize social robot tutors in natural education environments, including classrooms, after school programs, and homes, large scale deployments need to be conducted to understand what pitfalls need addressing. Another concern in making the technology of robot tutoring agents effective in impacting educational outcomes has to do with the high cost of robot tutoring platforms in their current form. Many studies involving robot tutors have used the Nao robot, which is commonly used as a platform in research labs, but is currently too expensive to be widely acquired by public school systems. The Keepon platform, which is more limited in its motion capabilities, but which has been shown to elicit social behaviors from children and has been successfully used in tutoring applications, may provide a more realistic option for a robot tutoring platform [127, 142]. The original Keepon platform was manufactured as a children's toy called myKeepon, which was then modified by robotics researchers to create a low-cost, programmable platform (toy platform plus additional parts cost approximately $250 in 2014). In addition, platforms must be built robustly, so that they can continue to function without breaking for extended use over long periods of time, withstanding the general amount of expected damage that commercial products for children must be able to endure. Investigating more affordable platforms that can handle the dynamic and unpredictable environment of children in learning is crucial in the pursuit of deploying robot tutors as real-world systems.

Additionally, there needs to be focus on the development of educational content and curriculum for robot tutoring systems that is generalizable. For systems that are deployed "in the wild" for longer periods of time, it may not be feasible to hand-design curriculum for specific educational domains. Instead, we should strive to create systems that can generate new content in an intelligent way, as well as focus on teaching high-level skills that transfer across domains. More systematic study and investigation into large scale deployments of robot tutors and their effectiveness in promoting learning over much longer time periods are necessary to understand whether the benefits of robot tutors can truly impact learning over time and whether this lasts once the support of the robot tutor has been removed.

7.3.6 Ethical Considerations

As we focus on building effective robot tutors for children and strive to deploy robust tutoring platforms to children in classrooms and homes, it is critical that we consider several ethical issues that arise. The first concern is about the dependence of students on robot tutors. Though we are building robot tutors that assist and provide support to students, it is challenging to study whether students form any type of dependence or attachment to the robot. As we are trying to build robot tutors to enhance learning and foster independence in learning, we must explore what happens when the robot's assistance or support is removed or faded in order to avoid indefinite reliance on the robot.

For very young children, early exposure to robots in educational settings may have additional consequences [208]. Most studies typically cite the effects of interacting with a robot tutor as an enjoyable, engaging experience for children, yet the majority of these studies consider single-session or shorter-term interactions. Tanaka et al. carried out a study in which toddlers engaged with a robot over several months (45 sessions) and found that children socially bonded with the robot and treated the robot more like a peer than a toy [217]. While this may be useful for learning in some contexts, children who are exposed to robots at an early age may form a dependence or attachment beyond the level that is intended, which could be harmful for the development or independence of the child. This is a practical concern of using robots in educational environments that should be considered when introducing social robots into scenarios involving very young children.

Another concern commonly brought up with regards to using robots as teachers is whether robots may replace teachers. The goal of building robust robot tutors is not to replace teachers, but rather supplement traditional classroom instruction with additional rich learning opportunities. Nonetheless, the social acceptance of robot tutors are crucial for their widespread adoption. Some research has investigated attitudes towards these types of technologies due to the fairly widely-held belief that robots could replace teachers or therapists [50]. Their work, which looked specifically at stakeholder acceptance of robots in autism therapy, indicated that people generally approve of using robots as therapy agents for children with autism when the human therapist is not replaced, and robots are used in conjunction with the therapist during a therapy session. Some work that has tried to evaluate the attitude of teachers towards robots for education found that educators seem potentially accepting of this type of technology, yet generally more cautious about the use of robots in school classrooms [117]. They also found that teachers had concerns about educational robots displaying appropriate social skills more than other ethical concerns or practical challenges of using robots in schools [117].

As technology generally advances and storage becomes more accessible and affordable, we are able to store more data about users in educational settings. Though cloud robotics may offer the potential to collect enough data to train machine learning models for robots to use in educational settings, this exposes sensitive data related to a child's education to privacy concerns. If robot tutoring systems are to be built as commercial platforms made for widescale use, they will require robust security systems that prevents educational data from being accessed without permission and protects privacy for various stakeholders involved in educational applications, such as students, parents, teachers, and education administrators.

7.4 Summary

This dissertation presents findings on how we can build personalized behaviors for robot tutors to effectively impact learning outcomes for children. It explores techniques to sustain engagement, support metacognitive strategy use, shape behavior, and proactively provide help during robot-child tutoring interactions. The well-controlled user studies we have conducted have generated several evidence-based design guidelines for building intelligent robot tutors. In addition, the model we designed and evaluated showed how we can utilize a unified computational framework to provide personalized help to students of varying skill levels. In all of the work presented in this dissertation, a central theme of the importance of personalization in designing robot tutor behavior emerges. The open questions and future work we describe outlines research to be conducted to further advance our knowledge of effective robot-child tutoring and sets the stage for robot tutors to be successfully used in classrooms and homes.

Chapter 8

Conclusion

Among the myriad technologies available, social robots have shown great promise as tutoring agents, especially for children. In this dissertation, we explored what types of personalized behaviors robot tutors can employ to enhance learning gains for children in one-on-one tutoring interactions. We sought to understand the impact of novel support strategies in robot-child tutoring by conducting several user studies over short-term and longer-term durations. We also contributed two more general architectures to designing robot intervention behaviors during tutoring: one that is more simple and relies on correlating measurements of user attributes to observable behavior, and one that computationally models the knowledge and engagement levels of the student and selects actions over time to maximize learning.

We conducted several user studies to better understand specific aspects of robot-child tutoring interactions, some which looked at one-session, short-term interactions (Chapters 3 and 4), and others which were conducted to evaluate methods for designing robot behavior over multiple-session, longer-term interactions (Chapters 5 and 6).

The results of the user studies we conducted provide novel insights and design recommendations for how to build effective, personalized robot tutors for children that positively impact learning outcomes. We investigated a practical mechanism for addressing a critical point in tutoring for children, namely sustaining engagement during a cognitively challenging interaction, and found that non-task breaks delivered based on performance changes can foster learning and restore attention during a tutoring interaction (Chapter 3). The work conducted in Chapter 4 was among the first to investigate robot tutors that support metacognitive strategy use, and demonstrated that both the robot platform and the think-aloud strategy itself fostered learning gains for students. We also found that robot tutors can be used to shape more productive behavior for students that lead to learning improvements, by showing that a robot tutor that countered unproductive help-seeking behavior helped students improve behavior and learning performance over several tutoring sessions (Chapter 5). In Chapter 6, we saw that robot tutors that provide help to students based on a model of the individual's knowledge and engagement levels are able to provide support in a much more personalized way to students of varying abilities, leading to improved learning performance and strategy use over a longer-term interaction.

We also contributed two architectures for designing robot behaviors that enhance learning within tutoring interactions, that can be applied more generally to a variety of learning settings. In Chapter 5, our architecture demonstrated the feasibility of designing simple, intuitive robot intervention behaviors that address unproductive user behavior based on measures of important user attributes. We validated this framework by highlighting the link between measures of user motivation and their suboptimal help-seeking behavior, and then employing a robot tutor that countered these suboptimal behaviors over four tutoring sessions. In our pursuit to build truly personalized robot tutoring systems that can handle learners of all different levels, we then built a computational model that maintained an estimate of each user's state and planned optimal help actions to provide to a given student (Chapter 6). This model can be applied more generally to a variety of supportive actions in tutoring and provides an integrated approach to student modeling and action selection over time. We evaluated this model in a long-term study, which revealed that personalized help action selection in a tutoring setting leads to better learning performance over time.

Appendix A

User Study Data: Test Scores

Below we present the test score data for each individual participant in each of the four user studies we describe in Chapters 3 through 6.

Table A.1: Pretest and posttest scores for participants in the user study referenced in Chapter 3.

Participant	Condition	Pretest Score	Posttest Score
1	Fixed	.75	.75
2	Fixed	.75	1.00
3	Fixed	.75	.75
4	Fixed	.00	.25
5	Fixed	.25	.25
6	Fixed	.00	.00
7	Fixed	.00	.00
8	Fixed	.00	.00
9	Fixed	.25	.25
10	Fixed	.25	.75
11	Fixed	.25	.00
12	Fixed	.75	.75
13	Reward	.00	.75
14	Reward	.50	.75

15	Reward	.00	.50
16	Reward	.00	.00
17	Reward	.00	.00
18	Reward	.75	.50
19	Reward	.25	.50
20	Reward	.00	.50
21	Reward	.00	.50
22	Reward	.00	1.0
23	Reward	.00	.75
24	Reward	.00	.25
25	Reward	.25	.50
26	Reward	.75	1.00
27	Refocus	.25	1.00
28	Refocus	.25	.50
29	Refocus	.50	.50
30	Refocus	.25	.75
31	Refocus	.25	.25
32	Refocus	.00	.00
33	Refocus	.00	.00
34	Refocus	.25	.75
35	Refocus	.50	.75
36	Refocus	.00	.25
37	Refocus	.25	.25
38	Refocus	.50	1.00

Table A.2: Pretest, posttest, and follow-up test scores for participants in the user study referenced in Chapter 4.

Participant	Condition	Pretest Score	Posttest Score	Follow-up Score
1	Robot&ThinkAloud	.17	1.00	.83
2	Robot&ThinkAloud	.50	.50	.83
3	Robot&ThinkAloud	.83	.83	.83
4	Robot&ThinkAloud	.67	.50	.83
5	Robot&ThinkAloud	.00	.00	.00
6	Robot&ThinkAloud	.50	.50	.67
7	Robot&ThinkAloud	.00	.67	.67
8	Robot&ThinkAloud	.67	1.00	1.00
9	Robot&ThinkAloud	.00	.00	.00
10	Robot&ThinkAloud	.00	.00	.17
11	Robot&ThinkAloud	.17	.50	.67
12	Robot&ThinkAloud	.83	1.00	1.00
13	Robot&ThinkAloud	.33	1.00	1.00
14	Robot-Only	.33	.67	.33
15	Robot-Only	.50	.83	.83
16	Robot-Only	.50	.83	.83
17	Robot-Only	.00	.17	.67
18	Robot-Only	.00	.00	.67
19	Robot-Only	.67	.83	.83
20	Robot-Only	.17	.50	.50
21	Robot-Only	.33	.67	.67
22	Robot-Only	.33	.33	.33
23	Robot-Only	.67	1.00	1.00
24	Robot-Only	.00	.00	.33
25	Robot-Only	.17	.17	.33
26	Robot-Only	.33	.83	.83

27	ThinkAloud-Only	.00	.00	.00
28	ThinkAloud-Only	.00	.17	.17
29	ThinkAloud-Only	.00	.00	.50
30	ThinkAloud-Only	.00	.00	.00
31	ThinkAloud-Only	.00	.00	.17
32	ThinkAloud-Only	.00	.33	.33
33	ThinkAloud-Only	.00	.00	.17
34	ThinkAloud-Only	.50	1.00	1.00
35	ThinkAloud-Only	.50	.00	.50
36	ThinkAloud-Only	.33	.33	.67
37	ThinkAloud-Only	.00	.50	.50
38	ThinkAloud-Only	.33	.83	.83
39	ThinkAloud-Only	.33	.83	1.00
40	Baseline	.00	.00	.00
41	Baseline	.00	.00	.00
42	Baseline	.00	.00	.00
43	Baseline	.17	.00	.33
44	Baseline	.00	.00	.17
45	Baseline	.83	.83	.83
46	Baseline	.17	.33	.33
47	Baseline	.33	.50	.50
48	Baseline	.00	.17	.00
49	Baseline	.00	.00	.00
50	Baseline	.00	.00	.17
51	Baseline	.33	.33	.50
52	Baseline	.00	.00	.00

Table A.3: Pretest and posttest scores for participants in the user study referenced in Chapter 5.

Participant	Condition	Pretest Score	Posttest Score
1	Control	.13	.25
2	Control	.88	.75
3	Control	.75	.88
4	Control	.38	.50
5	Control	.50	.88
6	Control	.00	.13
7	Control	.75	.75
8	Control	.75	.75
9	Control	.25	.50
10	Control	.63	.38
11	Control	.50	.38
12	Control	.38	.75
13	Control	.50	1.00
14	Control	.88	.75
15	Control	.38	.50
16	Intervention	.63	1.00
17	Intervention	.25	.75
18	Intervention	.00	.25
19	Intervention	.50	.50
20	Intervention	.13	.75
21	Intervention	.63	.88
22	Intervention	.75	1.00
23	Intervention	.00	.13
24	Intervention	.00	.25
25	Intervention	.38	.63
26	Intervention	.75	.88

27	Intervention	.25	.25
28	Intervention	.13	.25
29	Intervention	.00	.63

Table A.4: Pretest and posttest scores for participants in the user study referenced in Chapter 6.

Participant	Condition	Pretest Score	Posttest Score
1	Fixed	.10	.30
2	Fixed	.30	.50
3	Fixed	.00	.00
4	Fixed	.60	.40
5	Fixed	.10	.50
6	Fixed	.30	.30
7	Fixed	.10	.20
8	Fixed	.50	.88
9	Fixed	.44	.56
10	Fixed	.94	.94
11	Fixed	.69	.81
12	Fixed	.56	.50
13	Fixed	.63	.75
14	Fixed	.94	.88
15	AT-POMDP	.00	.30
16	AT-POMDP	.00	.20
17	AT-POMDP	.00	.30
18	AT-POMDP	.00	.80
19	AT-POMDP	.50	.60
20	AT-POMDP	.10	.20
21	AT-POMDP	.20	.40
22	AT-POMDP	.00	.13
23	AT-POMDP	.94	1.00
24	AT-POMDP	.31	.56
25	AT-POMDP	.00	.38
26	AT-POMDP	.81	.88

27	AT-POMDP	.88	1.00
28	AT-POMDP	.44	.63

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