Enhancing the Affordances of a Tangible Learning Environment through Prompts Delivered through a Teachable Robotic Agent

by

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A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved April 2014 by the
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ARIZONA STATE UNIVERSITY

May 2014

ABSTRACT

For this master's thesis, a unique set of cognitive prompts, designed to be delivered through a teachable robotic agent, were developed for students using Tangible Activities for Geometry (TAG), a tangible learning environment developed at Arizona State University. The purpose of these prompts is to enhance the affordances of the tangible learning environment and help researchers to better understand how we can design tangible learning environments to best support student learning. Specifically, the prompts explicitly encourage users to make use of their physical environment by asking students to perform a number of gestures and behaviors while prompting students about domain-specific knowledge. To test the effectiveness of these prompts that combine elements of cognition and physical movements, the performance and behavior of students who encounter these prompts while using TAG will be compared against the performance and behavior of students who encounter a more traditional set of cognitive prompts that would typically be used within a virtual learning environment. Following this study, data was analyzed using a novel modeling and analysis tool that combines enhanced log annotation using video and user model generation functionalities to highlight trends amongst students.

ACKNOWLEDGMENTS

I would like to first thank my chair, Winslow Burleson, for his feedback, support, and guidance regarding my research. Additionally, I would like to thank my committee members Arthur Glenberg, Erin Walker, and Katarzyna Muldner for their high-level of involvement throughout this research project and the mentorship and valuable insight they each provided. Also, I would like to thank the students who took the time to participate in this project. Without them, the knowledge gained from this master’s thesis would not be possible. Finally, I would like to thank my friends, family, and loved ones who have provided a great deal of moral support and encouragement throughout my post-graduate studies.

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CHAPTER 1

INTRODUCTION

Current research into new educational technologies is exploring how non-traditional learning environments, such as tangible learning environments and learning environments that support physical embodied interactions, can affect student learning. Previous work has shown that there is a connection between gesturing and the types of solutions produced by students (Beilock and Goldin-Meadow 2010). In Tangible Activities for Geometry (TAG), a tangible learning environment developed at Arizona State University, students have the opportunity to solve a variety of geometry problems by moving around a physical Cartesian plane.

However, although tangible learning environments provide students with an opportunity to utilize a wide variety of actions and gestures, they often lack structure (Walker & Burleson 2012). In TAG, to provide students with an appropriate level of structure while also maintaining an atmosphere of discovery, researchers have introduced a teachable robotic agent named Quinn. By framing problem-solving with a teachable agent framework, the system strikes a balance between providing students with an opportunity to explore in an open-ended learning environment and providing the necessary scaffolding and structure for students to progress at a reasonable pace (Muldner et al. 2013).

In addition to the intersection of tangible learning environments and a teachable agent framework, there are other aspects of this tangible learning environment that we believe can be manipulated to increase learning gains. For example, many learning environments use some type of feedback mechanism to help scaffold students through the learning process. Some examples of feedback strategies commonly used by systems with teachable agents include cognitive prompts, reflective questioning, and agent quiz/query capabilities. We believe that by developing a unique feedback strategy specifically designed to be used within a tangible learning environment, we can enhance learning more than if we were to use a general feedback strategy. Specifically, to maximize the potential of learning environments that support gesturing and other physical behaviors, we have developed a set of cognitive prompts that also prompts students to use gestures and behaviors that have the strongest effect on learning (Goldin-Meadow, Cook, and Mitchell 2009).

Our prompts are designed to not only scaffold learning, but also prompt students to use specific physical embodied interactions during the problem solving process, increasing their overall level of physical activity while using TAG. By encouraging students to utilize different types of embodied gestures and behaviors as they interact with their environment, we hope to combine the benefits of traditional forms of cognitive feedback with the potential benefits of tangible learning environments to improve learning gains. We believe that this will allow students to take advantages of the affordances of the tangible learning environment in addition the benefits of scaffolded cognitive support. In this way, our research expands on the existing body of work regarding scaffolding and cognitive prompts and investigates the interesting intersection of scaffolding, gesturing, and tangible learning environments.

CHAPTER 2

BACKGROUND AND THEORY

2.1 Tangible Learning Environments

Although learning theory supports the idea that utilizing physical embodiment in a tangible learning environment has the potential to enhance learning, little work has been done demonstrating how a tangible learning environment can be designed to encourage useful physical gestures and behaviors from students. Research in psychology and education has identified some of the specific affordances of tangible learning. For example, it has been demonstrated that young learners can sometimes physically demonstrate understanding of concepts before they have the ability to describe them (Bruner et al. 1966). Additionally, the hands-on manipulation of physical objects as part of the learning process can be helpful to students, specifically in more abstract domains, by allowing students to work with concrete examples before moving into the realm of the abstract (Chao et al. 2000). Together, these affordances can help students create representational mappings between the physical objects within their tangible learning environment and more conceptual information (Marshall 2007).

Despite this, tangible learning environments as a whole have not been investigated as thoroughly as other types of learning environments, such as virtual learning environments (Marshall 2007). We do not know specifically what type of problem-frameworks work best in these types of systems or what types of feedback mechanisms would be most beneficial to students working within a tangible learning environment. The most striking aspect of tangible learning environments is that they are unique in that they provide us an opportunity to encourage the use of a wide variety of physical embodied actions during problem-solving. However, to optimize learning within these systems, it is not enough simply for students to have the opportunity to physically engage with their environment. Researchers must also design learning environments that are actively encouraging learners to take advantage of the affordances of a tangible learning environment. Previous work has identified several effective strategies that have been successfully incorporated into virtual learning environments. Below we will discuss a subset of these strategies that we believe could be integrated into future tangible learning environments to help improve the effectiveness of these systems.

2.2 Teachable Agent Framework

Teachable agents have been used in learning systems as a way to scaffold students as they learn new concepts, guiding students to reflect on their ideas and helping to deepen their understanding of material by reinforcing key concepts (Pareto et al. 2011). The teachable agent framework utilizes the process of "learning by teaching" and tasks users with teaching or tutoring a computerized agent that plays the role of tutee. Similar to how a student who is required to tutor one of their peers typically is more motivated to learn the material thoroughly, students who work with teachable agents are often more focused and demonstrate more significant learning gains than their peers who learn material through traditional classroom environments (Leelawong et al. 2002).

2.3 Embodied Cognition through Gestures

Existing work done in the field of embodied cognition tells that gesturing and other physical behaviors can be very beneficial to learning. For example, Martin and Schwartz found that encouraging young children to physically interact with their environment can allow them to solve problems that they cannot yet solve “in their heads” and can help generate ideas that guide them when they encounter more symbolic, abstract versions of the same problem later (O'Malley and Fraser 2004). However, in this work students were not scaffolded to link their embodied behaviors with specific learning concepts. Additionally, researchers have found that the type of gestures employed by a learner during problem solving influences the strategy they choose to use (Alibali et al. 2011). This suggests that to maximize the potential benefits of a tangible learning environment that supports physical embodied user interactions, it is important not only to allow for embodied interactions, but also to encourage students to utilize the available interactions in a way that supports concepts being explored within the learning environment.

2.4 Cognitive Prompts

Using research done with other types of learning environments, we know that feedback is an essential part of the learning process (Shute 2008). Specifically, scaffolding tools such as cognitive prompts help to encourage additional reflection, deeper thinking, and higher quality learning. However, these prompts do not always encourage learners to embody the concepts they are trying to help teach. To provide this link between physical embodiment and abstract concepts, we propose creating a set of cognitive prompts that are delivered to students through a teachable, robotic agent in a tangible learning environment. These prompts will link embodied behaviors with various geometry concepts, providing us an opportunity to study physical embodiment in what is generally considered an abstract field (Alibali and Nathan 2012).

CHAPTER 3

SYSTEM

3.1 Using Tangible Activities for Geometry (TAG)

Tangible Activities for Geometry (TAG) is a tangible learning environment currently being developed at Arizona State University targeting middle school students that allows users to practice solving various types of geometry problems. TAG consists of three main components, which can be seen below in Figure 3.1.

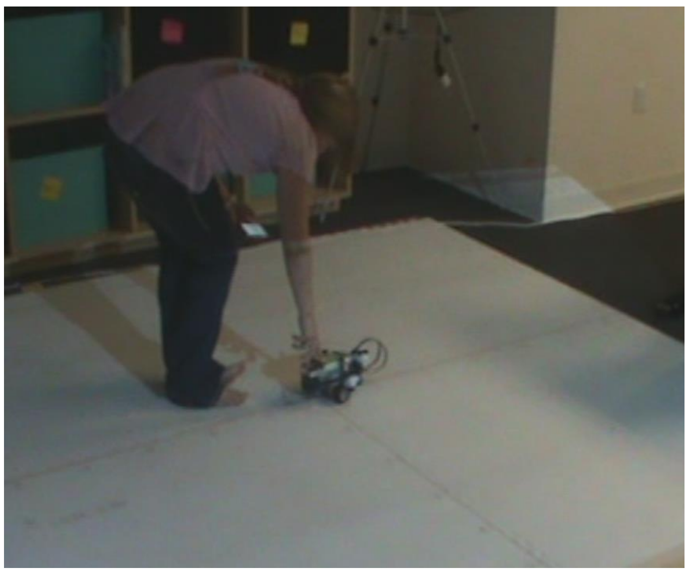

Figure 3.1 Photo of user interacting with main components of TAG: the tangible problem space, the mobile student interface, and the teachable robotic agent

Tangible Problem Space

The first component, the problem space, is a physical space that displays a projection of the geometry application Geogebra. This application provides students with a Cartesian plane which contains elements such as points and lines the student can interact with.

Students have the ability to walk around the problem space and can interact with the teachable robotic agent whom they are teaching about various geometry concepts.

Teachable Robotic Agent

Teachable agents help students learn by letting students try to teach concepts to an agent that simulates a traditional student tutee (Roscoe, Wagster, and Biswas 2008). Unlike learning frameworks where a traditional teacher is instructing students, teachable agents have been show to help students reflect, elaborate and refine their knowledge more extensively (Muldner et al. 2013). Quinn, the teachable robotic agent developed for this project, is a Lego Mindstorms robot who communicates with students through a second iPod Touch that is physically mounted on its robotic body. The robot's iPod interface consists of a clickable face which students can touch to bring up a list of actions on the mobile interface. Quinn can also use its interface to speak to students through both voice and text. Users are asked to solve problems within this system by providing Quinn with step-by-step instructions on how to solve each problem. A breakdown of a problem students might encounter in TAG and a set of steps to solve that problem can be seen in Table 3.1.

Plot a point at (3, -2)	1. Select Quinn and instruct it to move 3 units
	2. Select Quinn and instruct it to turn 90 degrees
	3. Select Quinn and instruct it to move 2 units
	4. Select Quinn and instruct it to plot a point

Table 3.1. An example of a problem students would encounter in TAG and the steps required to teach Quinn the correct solution.

Mobile Student Interface

The second component of this system is the mobile interface. Displayed on an iPod Touch, this interface provides the student with information from the system while also receiving input from students. For example, some functionalities of this interface are to display the current problem description and allow students to give commands to the third component, an interactive, teachable robotic agent..

3.2 Feedback Mechanisms

In TAG, both the system and Quinn have the ability to communicate to the students as they are solving problems through auditory and visual means. However, the existing feedback mechanisms within TAG incorporated little to no physically embodied elements, and were not taking full advantage of the additional affordances provided by a tangible learning environment. For example, we can use existing feedback mechanisms to provide social responses to correct and incorrect solutions as described in the discussion of agent attribution messages below. However, this type of feedback does not necessarily encourage students to gesture or use the physical space around them. To address this, a set of cognitive prompts designed to be delivered through Quinn have been implemented and take advantage of the affordances of the tangible learning environment by incorporating physically embodied actions into traditional cognitive prompts.

System Correctness Feedback

When a student believes they have guided Quinn to the correct solution, they have the option to check their solution for correctness. The student is then provided with correctness feedback on the mobile interface. In the event of a correct solution, students see a large image of a check mark, see a statement stating "...", and hear drumroll which indicates successful completion of the problem. If an incorrect solution is submitted, students see a large image of an x mark, see a statement stating "...", and hear buzzer which indicates unsuccessful completion of the problem.

Agent Attribution Messages

The attribution messages are delivered to students through voice and text in the robot interface. Whenever the student chooses to check their current solution, Quinn will randomly choose an attribution message from one of two pools. Quinn is programmed with eight attribution messages to be used after students have correctly solved a problem and eight different attribution messages to be used after students have submitted an incorrect solution to the system. An example of an attribution message to be used both after a correct solution submission and an incorrect solution submission can be seen in Figure 3.2

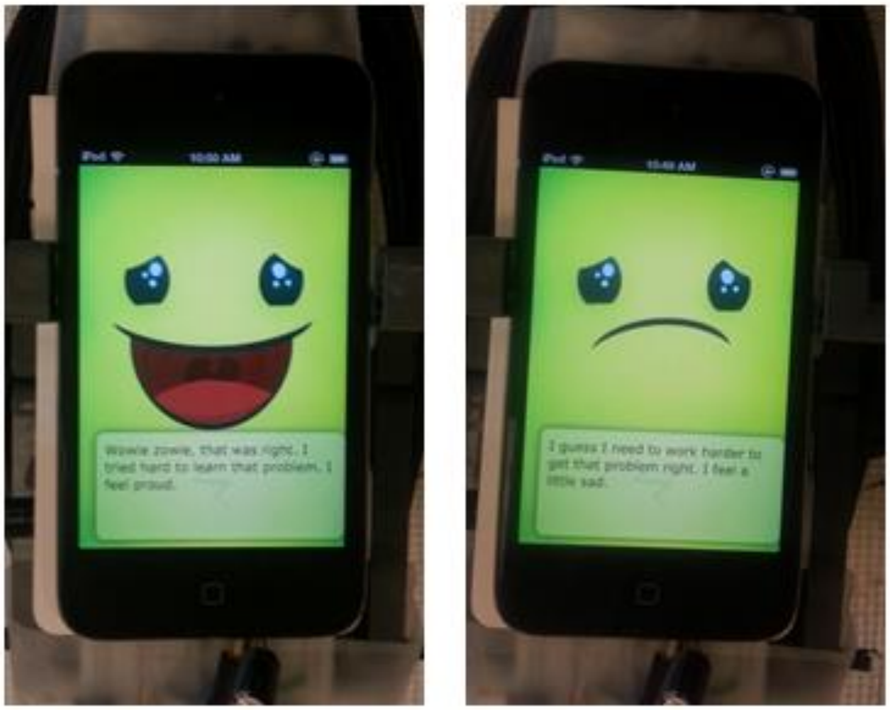

Figure 3.2 Photo of attribution messages delivered to users after a correct solution is submitted (left) and after an incorrect solution is submitted (right) through Quinn

The attribution messages in each of the two pools attribute success and failure along two different dimensions, the I-WE- YOU dimension and the EFFORT-ABILITY dimension. For this study, the pools of attribution messages were created based on a previous study conducted during Fall 2013. In this study, student perceptions and reactions to agent attributions along each of the above dimensions were analyzed to determine which types of attribution messages were favored by students. Based on the analysis from this student, the experimenters choose to utilize the following set of prompts, shown below in Table 3.2.

CORRECT attribution messages

Dimensions	Message Text
YOU-ABILITY	Yay! I got that right because you are a good teacher. I feel grateful.
YOU-ABILITY	I got that problem right and I have you to thank! You are so good at teaching.
I-EFFORT	Wowie zowie, that was right. I tried hard to learn that problem. I feel proud.
I-EFFORT	I'm glad I put in a lot of effort on that problem. I feel like I achieved something!
YOU-EFFORT	Holy cow, you worked hard at teaching me that problem.
YOU-EFFORT	Not very many teachers try as hard as you to help me learn! I feel grateful.
WE-EFFORT	Yay! We worked hard to solve that problem. I feel happy.
WE-EFFORT	Cool! We worked together to complete that problem.

INCORRECT attribution messages

Dimensions	Message Text
WE-EFFORT	Darn it. We did not try very hard on that problem. I feel sad.
WE-EFFORT	We did not put too much effort into figuring out that problem.
WE-EFFORT	Rats. We got that wrong because we did not work hard on that last one. I feel a bit down.
WE-EFFORT	Oh no! We must not have tried hard enough on that last problem.
I-EFFORT	That was wrong. I didn't think enough on that problem.
I-EFFORT	I feel responsible for that last one - I did not work enough to get it right.
I-EFFORT	I guess I need to work harder to get that problem right. I feel a little sad.
I-EFFORT	Oh boy. I got that wrong because I did not try hard to learn. I feel a little guilty.

Table 3.2 Attribution messages for correct and incorrect solution submissions along with their corresponding I-WE-YOU dimensions.

CHAPTER 4

EMBODIED PROMPTS

For this master's thesis, two sets of prompts were designed to encourage students to embody the abstract mathematical concepts they are required to learn to be able to tutor the teachable robotic agent, Quinn. Specifically, a set of ABSTRACT prompts was designed that prompted students to mentally embody concepts while a second set of ACTION prompts was designed to encourage students to physically embody targeted geometry concepts. The design process and implementation of these prompts within the TAG system is described below.

4.1 Original Adaptive Design

Originally, the prompts developed to be used within the TAG system were designed to align with specific problem solving steps in a given problem. For example, Table 4.1 shows a sample problem, the minimal steps required to obtain the correct solution for that problem, and prompts mapped to specific steps in that solution path.

This design allowed for prompts to address common mistakes that students would make at specific steps in the problem-solving process. For example, when moving Quinn to a negative x-coordinate, students could receive a prompt reminding them that the negative x-values are on the left side of the Cartesian plane.

Steps	EMBODY THROUGH ACTION (correct)	EMBODY THROUGH ACTION (incorrect)	THINK ABSTRACT (correct)	THINK ABSTRACT (incorrect)
Begin problem	Can you show me which axis the 4 in (4, 0) tells me to move on?		In (4, 0), does the 4 tell me to move on the x-axis or on the y-axis?	
Start facing 90°				
Move 4 units				
Plot point	Come over here an see the point I plotted at x = 4 and y = 0		I plotted a point at x = 4 and y = 0	I plotted a point at x = __ and y = __
Verify answer correct	Neat! Now I know that the first number tells me to go left or right on the x-axis! Can you point left and right on the x-axis?		Neat! Now I know that the first number tells me to go left or right on the x-axis!	
	Hey can you show me where 4 is on the x-axis again?	[x-position incorrect] Hey can you stand where 4 is on the x-axis?	Where is 4 on the x-axis again?	
		[y-position incorrect] Hey can you stand where 0 is on the y-axis?		

Table 4.1 Example of original adaptive prompts developed for TAG

However, due to the extra time required to implement this type of prompt design and the time constraints imposed by a previously scheduled study using the TAG system, this type of prompt design could not be implemented for the study run for this master's thesis. Instead, the design work done with these adaptive prompts will be continued and implemented for future versions of the TAG system and the effectiveness of these adaptive prompts will be tested in future studies.

4.2 Targeted Concepts and Misconceptions

The prompts that were implemented and tested as part of this master's thesis were designed to target five unique corresponding misconceptions that were identified during the analysis of results from a previous study with the TAG system. Each misconception was identified using the modeling and analysis tool described in the next chapter.

4.3 Current Design and Implementation

Design

Following the decision to move away from adaptive prompts for the purpose of this master's thesis, the original adaptive prompts designed to be incorporated into the TAG system were redesigned for a non-adaptive implementation. To do this, prompts were generalized to fit any problem solving step in any of the sixteen problems students could encounter while using TAG.

The wording of the prompts was designed to vary the level of physical embodiment encouraged within individual prompts to see if prompting students to think about concepts in a physically embodied way while simultaneously prompting students on domain content has an effect on student learning. To do this, we have designed two sets of prompts. The first set incorporates various action verbs that prompt students not only to think more deeply about various geometry concepts, but also to demonstrate their understanding of these concepts through embodied actions. The second set of prompts targets various geometry concepts, but does not explicitly ask students to perform any type of physical action or gestures. Although the prompts that require students to mentally embody concepts still allow for reflection and revision of ideas, they do not take advantage of all of the affordances of a tangible learning environment. Specifically, they do not encourage students to utilize gestures that can help to bring out implicit knowledge (Alibali et al. 2011). An example from each set of prompts can be seen below in Table 4.2.

		Prompt Sets	
Targeted Geometry Concept	**Corresponding Geometry Misconception**	**ACTION - prompts students to physically embody concepts through explicit behaviors and gestures**	**ABSTRACT - prompts student to think about concepts mentally**
To the right of the x-axis all x's are positive/to the left of the x-axis all the x's are negative.	Invert x-axis. The student moves negatively when they should move positively and vice-versa.	"I'm trying to remember where all the x's are positive. Can you walk to a part of the graph where all the x's are positive?"	"I'm trying to remember where all the x's are positive. Where on the graph are the x's all positive?"

Table 4.2 Example of cognitive prompts from the ACTION and ABSTRACT prompt sets developed for TAG

The targeted geometry concepts and corresponding geometry misconceptions were chosen based on the results of a previous study using the TAG system that was completed in Fall 2013.

Implementation

To make the scope of this project more manageable, the implementation of the prompts was changed from an adaptive delivery system to a time-based delivery system through which Quinn would give students a new prompt no sooner than two minutes since the previous prompt was received. This allowed for i) the reasonable control of the number of prompts that students would encounter during a 45 minute usage session and ii) reduction in the number of hours required to program the prompt delivery system and incorporate it into the existing TAG architecture. Every time students complete an action within TAG, a check is performed to determine when the last cognitive prompt was delivered to the student. If it has been at least two minutes since the last prompt was encountered, a new cognitive prompt is randomly delivered to the student. This delivery system allows the cognitive prompts to be delivered to students at different states of the problem with the possibility that more than one prompt will be encountered in a single problem, giving students an opportunity to reinforce and evaluate their understanding of concepts presented in a given problem more than once (Thomas et al. 2013).

Delivery Mechanics

The prompts are delivered to students through voice and text in the robot interface, as shown below in Figure 4.1. Presenting this type of cognitive feedback through more than one format provides students with multiple opportunities to process information and has been shown to be beneficial to learning (Dirkin, Mishra, and Altermatt 2005). We also choose to deliver these prompts through Quinn rather than through the system messages delivered through the mobile interface because prior research has shown that when teachable agents provide active feedback to their student tutees, there is a positive effect on learning (Biswas et al. 2010).

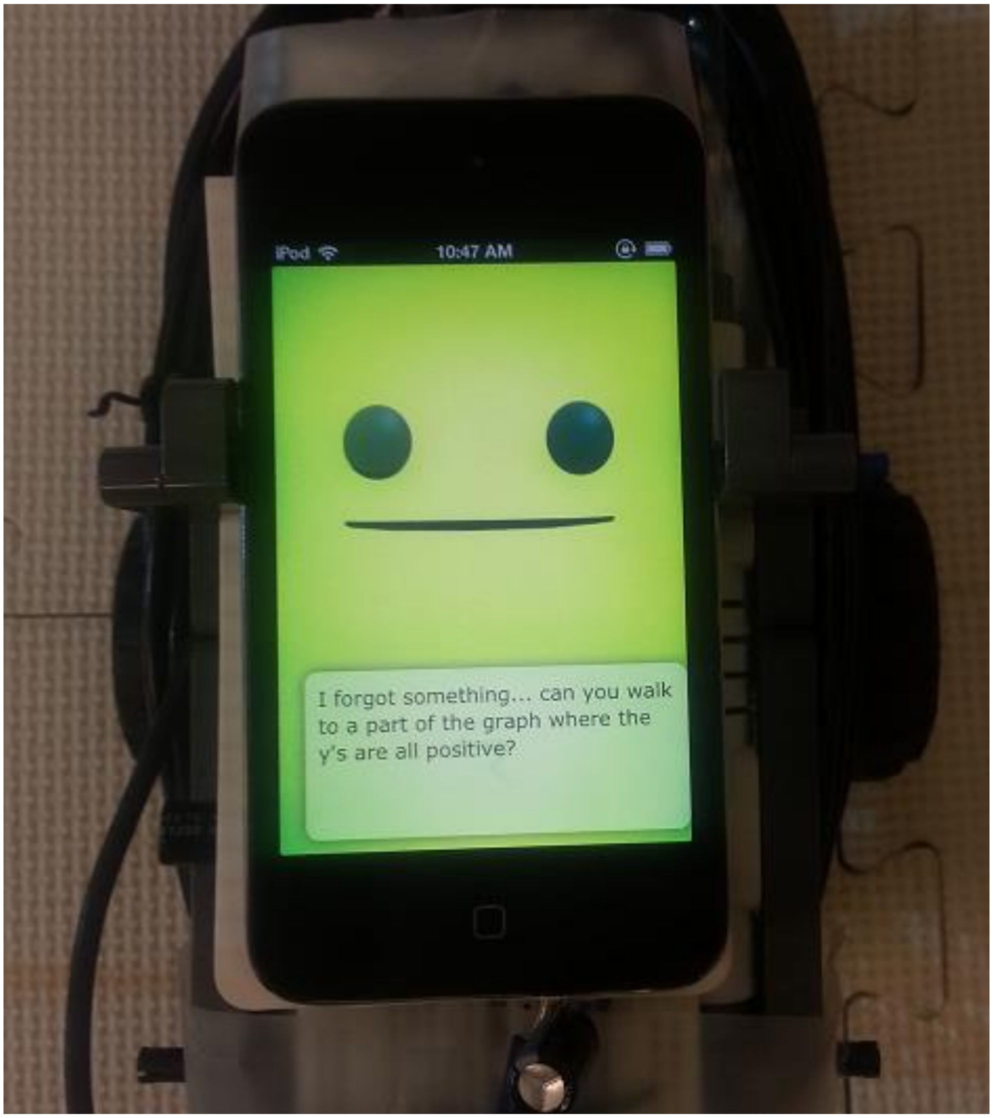

Figure 4.1 Photo of cognitive prompt messages delivered to users through Quinn during problem solving in the ACTION condition.

CHAPTER 5

MODELING AND ANALYSIS TOOL

5.1 Purpose of Tool

The purpose of the modeling and analysis tool described below is to allow for easy annotation of automatically generated log files using video analysis that can then be used to automatically create labeled graphs illustrating the behavior patterns of subjects. Integrating these functionalities into a single tool will streamline data analysis as the amount of data produced by emerging educational technologies increases (Romero, Ventura & García, E., 2008). During the analysis process, these behavior modeling capabilities will allow for the identification of common strategies, common misconceptions, and interesting trends in students' behavior models.

5.2 Description of Features

The tool was developed using Java Swing and utilizes the *vlcj* and *Jung* libraries. There are two main components to the analysis tool: a log annotation and video analysis frame and behavior graph view, shown below in Figure 5.1. Each section is described in more detail below.

Video Analysis and Log Annotation

The first is the log and video annotation feature. Users can load .csv log files and a number of supported types of video files, which will then be displayed on the left side of the interface, as shown in Figure 5.1. As users replay session videos, the tool automatically scrolls through the log file loaded by the user, using timestamp information from the log file and video to highlight the action in the log file currently being viewed in the video. Alternatively, users can select a specific action in the log file and use the tool to jump to the corresponding part of the video. Users also have the ability to annotate their log files by adding new row or column information or editing existing data fields. These annotations are then used by the tool's automatic graph generation feature to visualize behaviors at different parts of students' solution models.

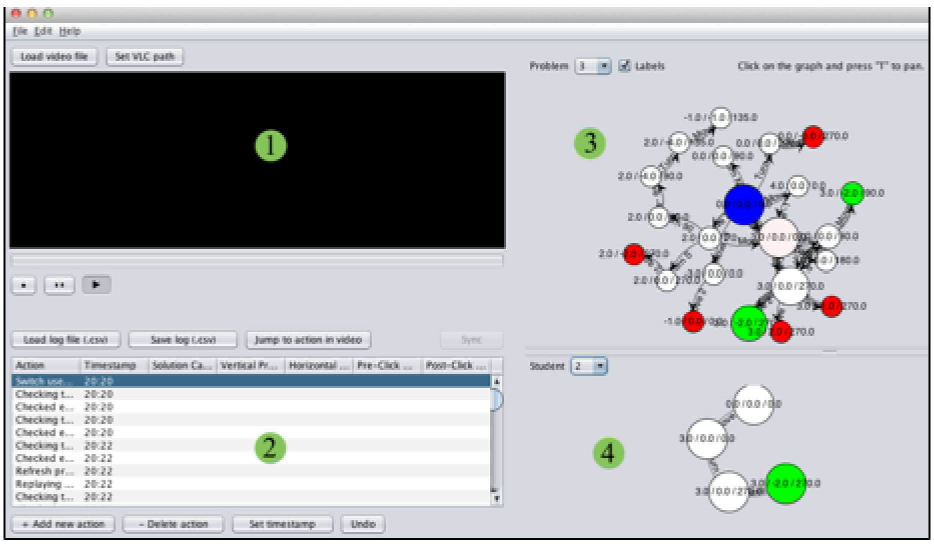

Figure 5.1 The modeling and analysis tool' s main interface showing (1) video player (2) log annotation field (3) aggregate behavior graph (4) individual behavior graph.

Graph Generation from Log Files

The second component of the tool is the student behavior graph generator. Using information from the log files, the tool compiles a model of the student(s) state and transition information as they use TAG, maps the annotations from video analysis to the model, and creates a behavior graph modeling their interaction with the system. Several dimensions of data visualization are utilized in the behavior graph including node size, node color, and edge thickness. The size of nodes and thickness of edges reflect the number of students that have passed through a particular state or transition in their individual solution model. Several colors are used to highlight specific node states. In this case, blue nodes represent the starting state, red nodes represent submission of an incorrect solution and green nodes represent submission of a correct solution. The researchers' annotations that are added to the log files are visualized on the behavior graphs using colored transitions, as shown below in Figure 5.2 Users of the modeling and analysis tool can toggle between which annotation category they would like to see visualized on the graph so see how the solution paths of students exhibiting a particular annotated behavior differ from the aggregate solution path.

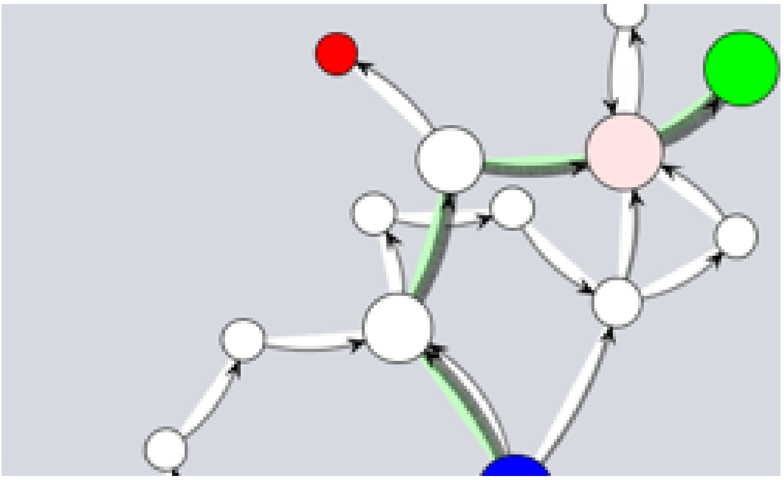

Figure 5.2 Graph showing transitions highlighted in green, indicating students who used those transitions exhibited the currently selected annotated behavior.

CHAPTER 6

HYPOTHESIS AND METHODOLOGY

6.1 Presentation of Hypothesis

There are several different variables that will be used to analyze the effectiveness of the prompts. First we will look at the performance accuracy of students in both the ABSTRACT and ACTION conditions. This will be measured by looking at the number of correct versus incorrect solutions students submit both during their time using the TAG system and during pre/post-test assessments. Second, we will look at performance efficiency, which will be measured by comparing the number of correct solutions generated during TAG system usage and pre/post-test assessments with the time taken by the student to create those solutions. Finally, we will look at both the frequency of and types of different physical behaviors students demonstrate during TAG system usage. Frequency will be a count of how many times students exhibit some kind of physical movement or behaviors while type will be a binary classification of static (the student's position on the Cartesian plane did not change) or non-static (the student's position on the Cartesian plane did change).

The analysis of the above variables will look to prove or disprove the following three hypotheses. First, we will seek to determine whether cognitive prompts designed to encourage physical actions to facilitate embodied cognition have an effect on the performance accuracy of students using TAG. By prompting students to take advantage of the affordance of their physical space while simultaneously providing cognitive prompts related to the domain content, students should be able to maximize benefits of embodying the content they are attempting to learn. It is hypothesized that encountering cognitive prompts that explicitly encourage movement within the physical space will help students build and retain more knowledge, leading to a higher performance accuracy than that of students who are presented with prompts that do not explicitly prompt students to move or gesture.

We will also compare the performance efficiency of students presented with the cognitive prompts designed to encourage physical actions with students presented with a more traditional, abstract set of cognitive prompts. The time taken for students to successfully complete individual problems is expected to be less for those students using the ACTION prompts because the gestures and actions they are prompted to use should help them to make connections and identify the problem-solving strategy they should be using.

Finally, we will compare the behavior models of students presented with the different types of prompts, focusing on the types and occurrences of physical gestures and movements. This comparison will allow us to determine if the cognitive prompts designed to encourage physical actions are prompting students to take advantage of the additional affordances of the tangible learning environment in which they are working. It is hypothesized that students who encounter prompts that are encouraging explicitly movements such as walking, pointing, and moving around a physical Cartesian plane will generate behavior models with more types and occurrences of physical gestures and movements than students who are presented with a more traditional, abstract set of prompts.

In summary, the three hypotheses this work will investigate are:

- H1: Students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will be able to solve problems more accurately than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors.
- H2: Students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will be able to solve problems more efficiently than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors.
- H3: Students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will demonstrate more occurrences of and types of physical gestures and movements than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors.

6.2 Methodology

The below sections will describe the experimental design of the study used to collect data on the effects of the cognitive prompts designed for the TAG system. Upon their arrival, participants were given an initial survey to gather information about background, comfort-level with geometry, and experience with mobile technology. Then, each participant was given a pre-test to measure their prior knowledge. Participants were randomly assigned to one of the two conditions. Each participant was led through a TAG system training session to familiarize them with how to interact with Quinn and solve problems using TAG. Once participants completed the training phase, they were given approximately 45 minutes to teach Quinn the solution to as many problems as they could. During this experimental phase, students were provided both with a reference guide listing directions on how to use the different commands available to them and solution cards that provided domain knowledge on how to solve all of the problems students could encounter during their session using TAG. When 45 minutes has elapsed, students are then asked to complete a brief post-test to gauge their domain knowledge after using the TAG system. The experimenter then conducts a short interview to gain information about the student's perceptions of the system.

Participants

The participants were currently in grades 5-6 and came from several schools in Tempe, Arizona. Ten participants were used, of which 6 were male and 4 were female. These participants were randomly assigned to one of the two conditions as shown in Table 6.1 below.

Physically embodied prompts explicitly encouraging gestures and movements while targeting domain concepts	**Abstract cognitive prompts targeting domain concepts**
3 male 1 female	3 male 1 female

Table 6.1 Gender distribution of participants randomly assigned to the two conditions.

Measures

An initial survey was given to students at the beginning of each session to record each subject's age, gender, level of comfort with mathematics and geometry, and prior experience with mobile technology.

After completion of the initial survey, students were given fifteen minutes to complete a pre-test to assess their prior knowledge of the content utilized by TAG. Results from this pre-test were then later compared to a post-test that assessed identical concepts.

Following the completion of TAG system training and a forty-five minute TAG experimental use session, students were given fifteen minutes to complete a post-test to assess their knowledge of the content utilized by TAG. Results from this post-test were then later compared to a pre-test that assessed identical concepts.

The exit survey questions and interview provided feedback regarding students' perceptions of the prompts and their usability.

6.3 Analysis Using Assessments Strategies and Modeling and Analysis Tool

The below section will describe how a novel graph modeling and video analysis tool was created and will be used to analyze the impact of the ACITON and ABSTRACT prompts developed for the TAG system. The analysis tool allows existing log files to be easily annotated and generates, for aggregated and individual log data, a behavior graph modeling the data represented in the log files.

Strategy for Analysis

There will be different axes on which analysis will be performed to assess the impact of the cognitive prompts developed for the TAG system. The performance accuracy and performance efficiency will be measured using automatically generated log data recorded during student sessions. The TAG system records the timestamps of all system and student actions, so we can utilize this data to determine the number of correct versus incorrect solutions a student submits and calculate the time students spend completing each problem they attempt. Additionally, pre and post-test scores will be used to analyze prior knowledge and learning gains, another component of performance accuracy.

After all sessions are completed, the log data can be utilized by the modeling and analysis tool to generate two different graph models for each of these axes, one highlighting performance accuracy through annotations, the other highlighting performance efficiency through annotations on the graph. The behavior models of students will be generated from additional annotation of the log files performed by the researchers. Using the video playback and log annotation feature of the modeling and analysis tool, researchers can record the type and frequency of different physical gestures and behaviors that students perform while attempting problems in TAG. Once video analysis is complete, the annotated logs can be processed by the modeling and analysis tool to generate graph models highlighting different aspects of students' behavior models through annotations on the graph.

CHAPTER 7

RESULTS

Analysis on the effect of the prompts on the student behavior and performance models was gathered using a novel video analysis tool described in Chapter 5 (Girotto et al. 2014). This allowed for both qualitative analysis of video from these sessions and modeling of student actions using the video analysis tool's unique graph generation capabilities.

7.1 H1 Results

H1 stated that, "students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will be able to solve problems more accurately than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors".

Aggregate Student Performance Accuracy during TAG Usage

To measure aggregate student performance accuracy of each pool, the number of correct solutions submitted by all students in each the ACTION and ABSTRCT pools was compared to the total number of solutions submitted by all students in same pool.

It was found that on average, of the 16 available problems students completed 9.67 problems successfully. During the average 43.11 minutes using TAG, students submitted an average of 13.22 solutions. Of all the solutions submitted, 67.22% of these were correct. Students who encountered prompts from the ABSTRACT pool during their use of TAG submitted an average of 8.25 correct solutions at an accuracy rate of 68.47 while students who encountered prompts from the ACTION pool submitted an average of 9.50 correct solutions at an accuracy rate of 60.56%. A comparison of each condition's average accuracy rate during TAG usage can be seen in Figure 7.1 below.

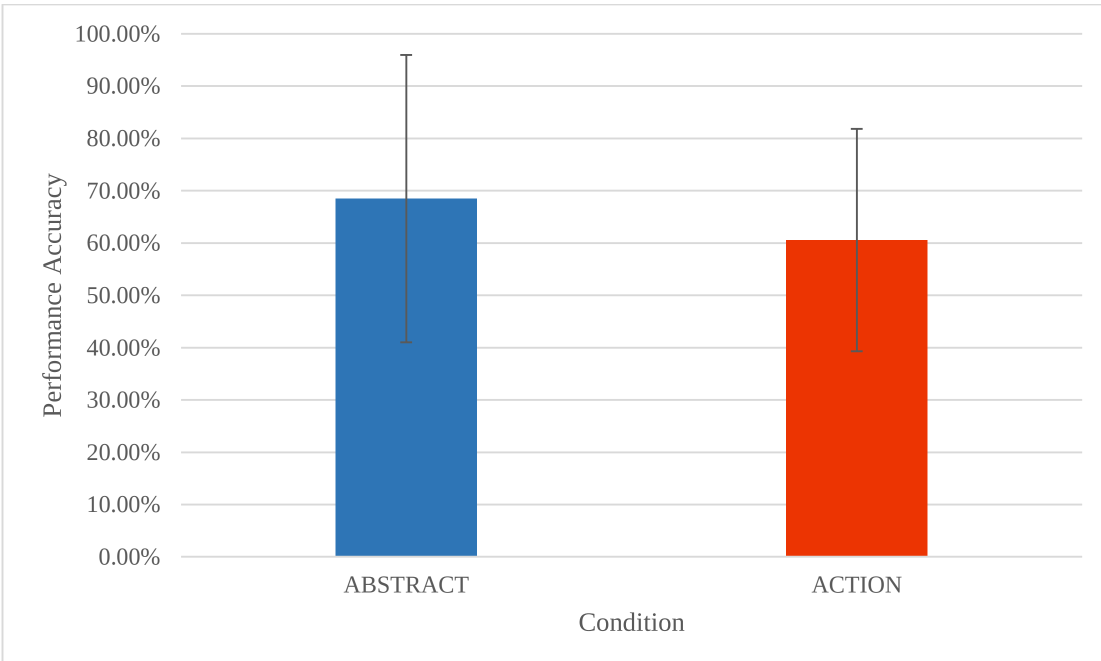

Figure 7.1 Performance accuracy of ABSTRACT and ACTION conditions during TAG usage

Aggregate Student Performance Accuracy during Pre/Post Test Assessments

To measure student performance accuracy on the pre-test and post-test assessments, the number of correct problems completed by each student was compared to the total number of possible problems (32) that students could complete. All problems were scored with a binary grading system – students could not receive partial credit for any problem.

It was found that on average, students scored 49.22% on the pre-test assessment and 61.72% on the post-test assessment. Students who encountered prompts from the ABSTRACT pool during their use of TAG scored an average of 59.38% on the pre-test assessment and an average of 71.88% on the post-test assessment. Students who encountered prompts from the ACTION pool during their use of TAG scored an average of 39.06% on the pre-test assessment and an average of 51.56%.

In both the ABSTRACT and ACTION conditions, students averaged an improvement of 12.50% between pre-test and post-test assessments. Because of the differences between the average pre-test scores of both conditions, an adjusted gains score measure was used to more accurately measure evaluate the students' improvement from pre-test to post-test assessment, Students in the ABSTRACT condition had an average adjusted gain of 36.11% while students in the ACTION condition had an average of 23.50%. This information as well as the average pre/post-test score in each condition, described in the previous paragraph, are illustrated in Figure 7.2 below.

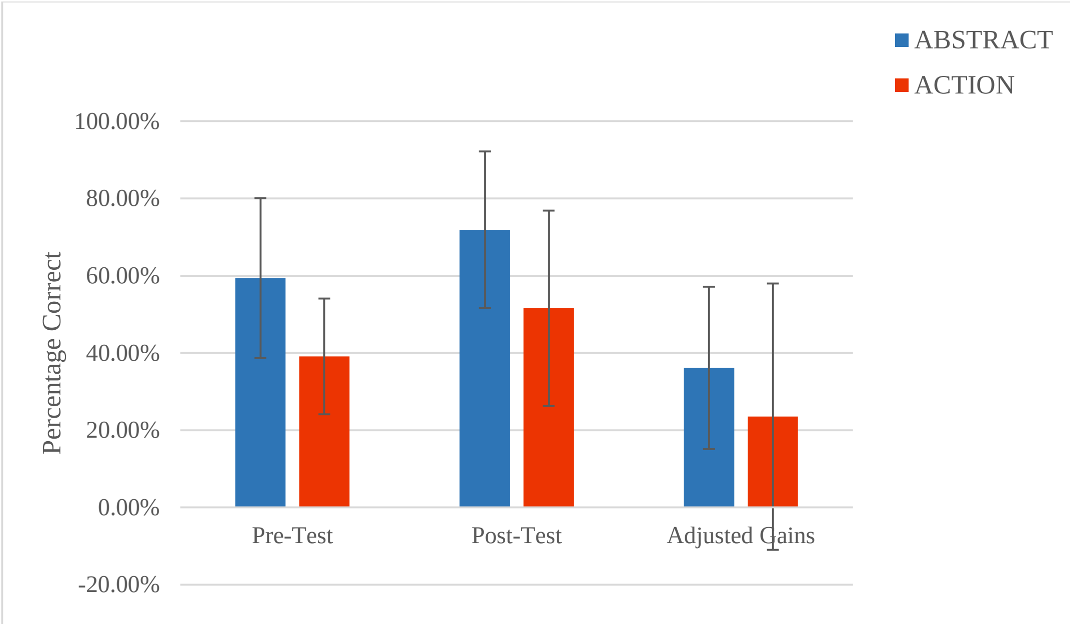

Figure 7.2 Performance accuracy of ABSTRACT and ACTION conditions during pre/post-test assessments including adjusted gain scores

There exists a negative correlation between the improvement of performance accuracy between pre-test and post-test scores and the amount of time spent on the post-test assessment. While subjects in the ABSTRACT pool spent an average of 3.50 minutes less on their post-test assessment than their pre-test assessment, subjects in the ACTION pool spent an average of 0.75 more minutes completing their post-test assessments. Implications of this will be discussed in Chapter 8.

Summary of H1 Results

The performance accuracy of students in the ABSTRACT condition was higher than the performance accuracy of students in the ACTION condition, using assessments to measure short-term learning gains.

7.2 H2 Results

H2 stated that, "students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will be able to solve problems more efficiently than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors".

Aggregate Student Performance Efficiency during TAG Usage

To measure aggregate student performance efficiency of each condition, the number of correct solutions submitted by all students in the ACTION and ABSTRCT pools was compared to the time spend using the TAG system by all students in the ACTION and ABSTRCT pools. Students in the ABSTRACT pool spent an average of 9.07 minutes per problem with a standard deviation of 6.88 while students in the ACTION pool spent an average of 6.75 minutes per problem with a standard deviation of 4.92. These results are illustrated in Figure 7.3 below.

Aggregate Student Performance Efficiency during Pre/Post-Test Assessments

Student performance efficiency was measured by comparing the number of correct problems completed by students, for both pre-test and post-test assessments, to the time taken to complete each assessment. During the pre-test assessment, students who encountered prompts from the ABSTRACT condition completed problems at an average rate of 0.63 minutes per problem while students who encountered prompts from the ACTION condition completed problems at an average rate of 0.97 minutes per problem.

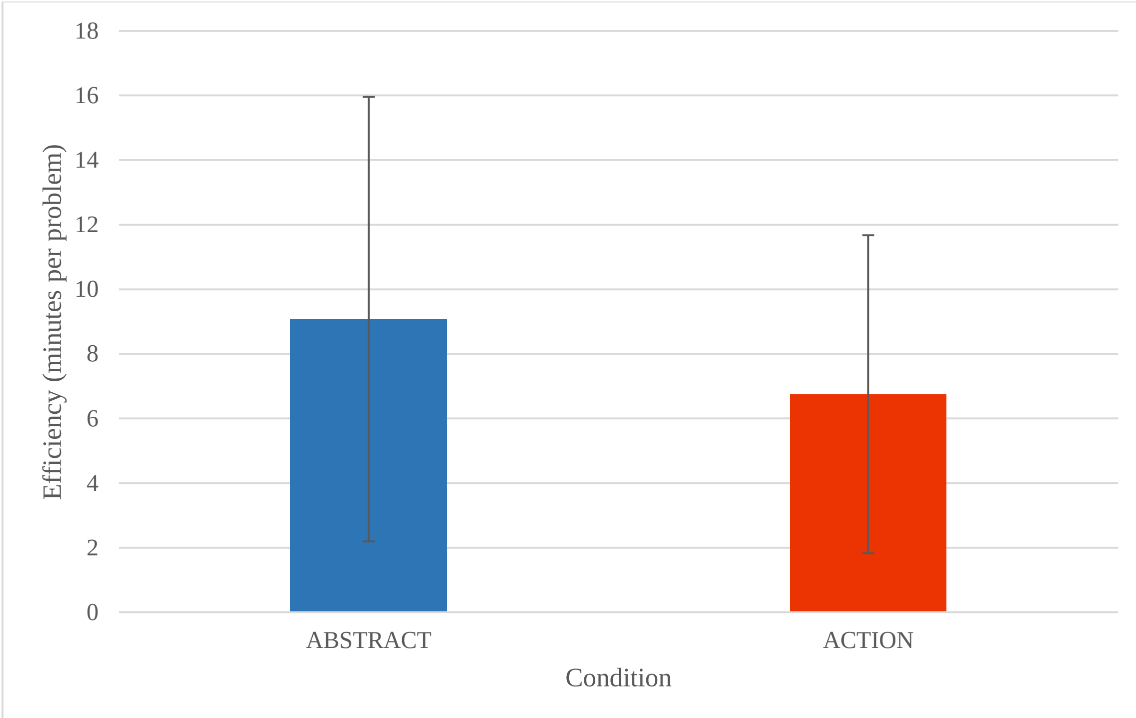

Figure 7.3 Performance efficiency of ABSTRACT and ACTION conditions during TAG usage

The performance efficiency of both groups of students increased during the post-test assessment where students who encountered prompts from the ABSTRACT pool completed problems at an average rate of 0.33 minutes per problem while students who encountered prompts from the ACTION pool completed problems at a rate of 0.89 minutes per problem. Students who encountered prompts from the ABSTRACT pool improved their performance efficiency by 0.39 minutes per problem while students from the ACTION pool only improved their performance efficiency by 0.16 minutes per problem.

Summary of H2 Results

The differences between performance efficiency for students' in the ABSTRACT and ACTION pools during TAG usage were minor. Similarly, the difference between performance efficiency for students' in the ABSTRACT and ACTION during pre/post-test assessments were minor.

7.3 H3 Results

H3 stated that, "students who are presented with cognitive prompts designed to explicitly encourage physical actions in a tangible learning environment will demonstrate more occurrences of and types of physical gestures and movements than students who are presented with prompts that do not explicitly prompt for these types of physical behaviors."

Aggregate Student Behavior Frequencies

To compare aggregate student behavior models, the type and number of occurrences of different types of actions and gestures exhibited by the students were added to the appropriate log files using the Modeling and Analysis tool. Then, this data was used to compare frequencies of different behaviors in each condition. A breakdown of the average frequencies of common behaviors can be seen below in Figure 7.4.

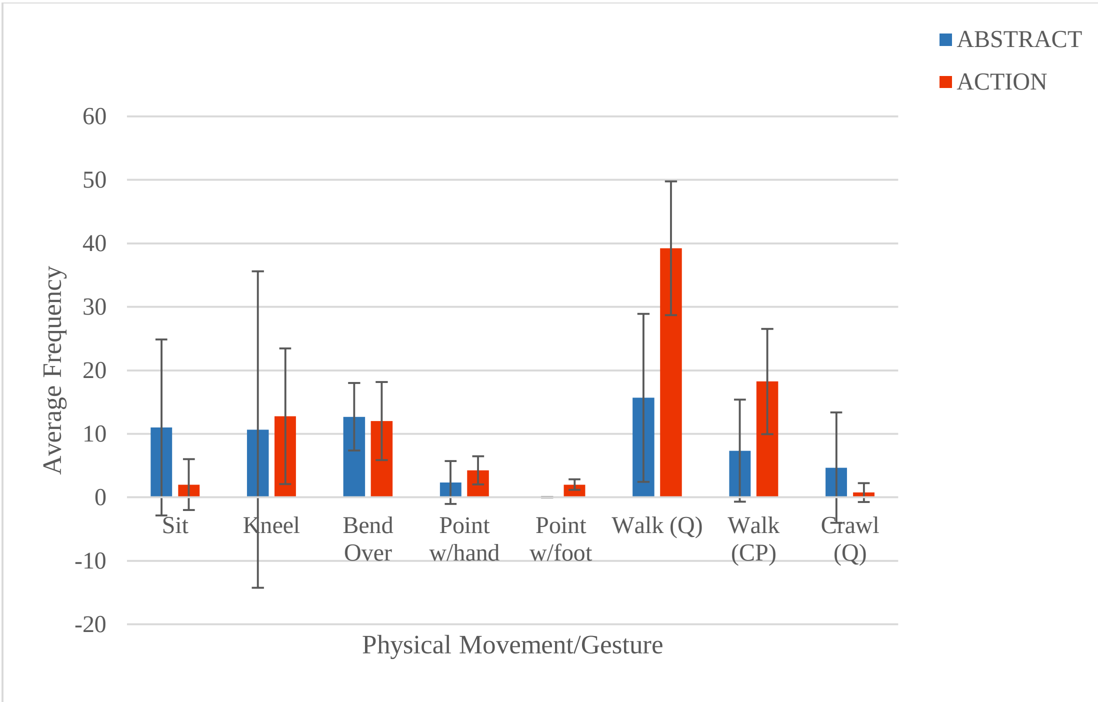

Figure 7.4 Aggregate average behavior frequencies of ABSTRACT and ACTION conditions during TAG usage

There are some distinct differences between the behaviors exhibited by the students in the ABSTRACT and ACTION conditions. Generally, students in the ABSTRACT condition tended to favor behaviors and positions that were closer to Quinn and the Cartesian plane. These behaviors include sitting on the Cartesian plane near Quinn, kneeling on the Cartesian plane near Quinn, and crawling across the Cartesian plane towards Quinn. Students in the ACTION condition tended to exhibit upright behaviors and animated gestures, including walking both towards Quinn and to different areas of the Cartesian plane, and pointing with extremities such as the hands or feet.

Summary of H3 Results

Major differences in the behavior models and gesturing patterns of students from each of the two conditions during TAG usage include both different types and different frequencies of various behaviors and gestures. Students in the ACTION condition tended to exhibit more physical behaviors – specifically non-static movement such as walking around the Cartesian plane and towards Quinn and static gestures such as pointing. Students in the ABSTRACT condition tended to use fewer behaviors and gestures and remain relatively close to the ground/Quinn during problem solving.

7.4 Process Analysis Results

In addition to evaluating the data collected pertaining the three original hypotheses, process analysis was performed using the modeling and analysis tool described in Chapter 5 to see if any patterns in student behavior were evident when looking at the aggregate solution models for the ABSTRACT and ACTION conditions.

Aggregate Student Behavior Models

To compare aggregate student behavior models, the type and number of occurrences of different types of actions and gestures exhibited by the students were added to the appropriate log files using the Modeling and Analysis tool. Then, this data was used to generate one aggregate behavior graph for all students in the ACTION condition and another for all students in the ABSTRACT condition. The tool's visualization feature was then used to highlight the occurrence of different physical behaviors along the student action on the graph during which the behavior occurred.

One key difference between the ABSTRACT and ACTION conditions was the part of the solution path at which students performed different kinds of behaviors. For example, in problem 2, students in the ABSTRACT condition tended to exhibit static behaviors like bending over the robot and kneeling next to the robot in the steps directly preceding the submission of a solution. This is shown below in Figure 7.5. However, students in the

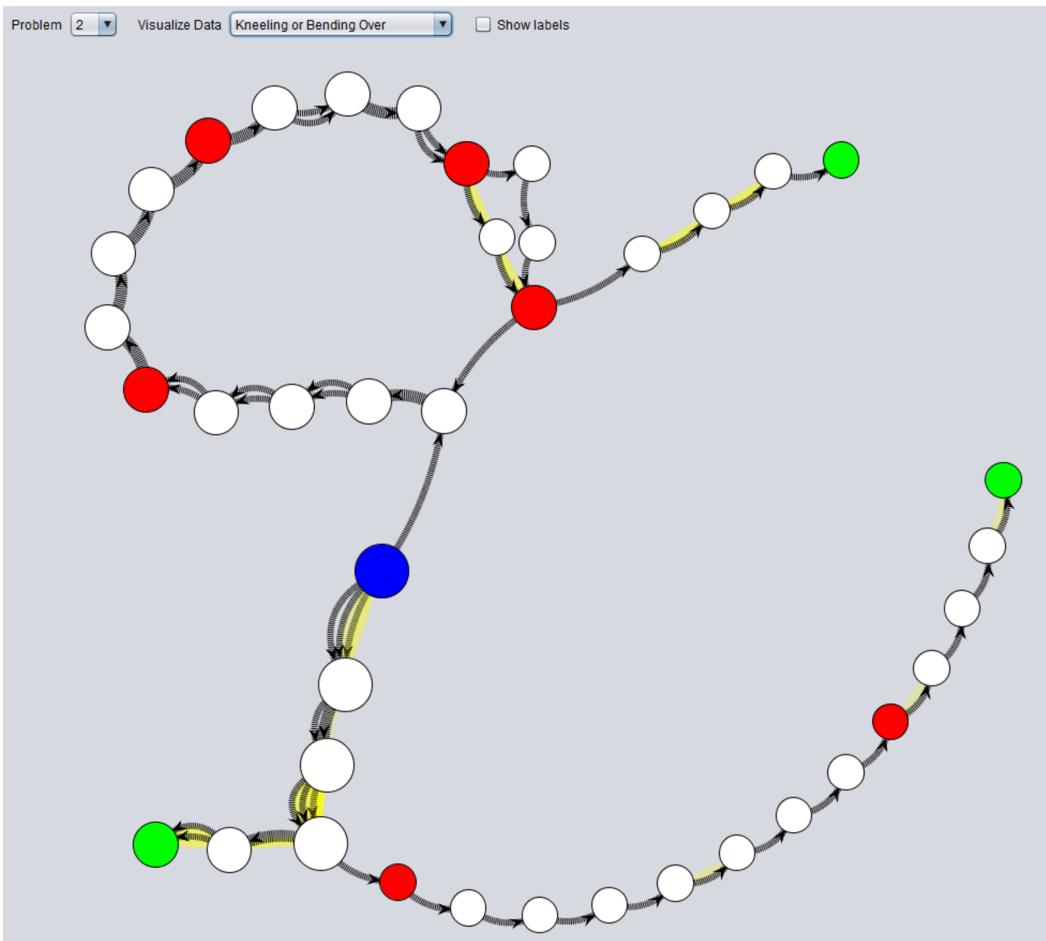

Figure 7.5 Aggregate graph for problem 2 modeling solution paths of students in the ABSTRACT condition with kneeling or bending actions highlighted in yellow.

ACTION condition, while sometimes exhibiting these specific static behaviors, did so less frequently and when they did exhibit these types of behaviors, they were less likely to directly precede the submission of a solution. An example of this is shown below in Figure 7.6.

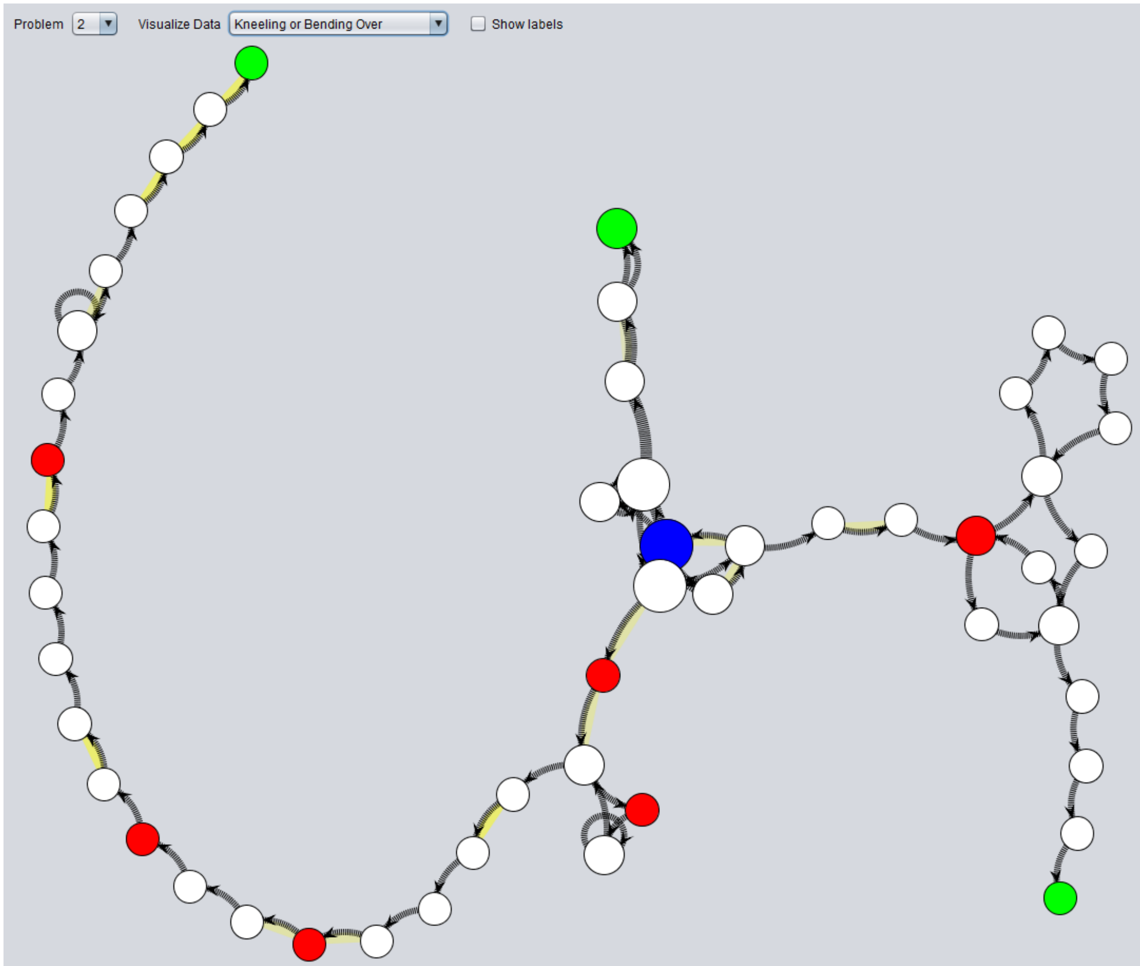

Figure 7.6 Aggregate graph for problem 2 modeling solution paths of students in the ACTION condition with kneeling or bending actions highlighted in yellow.

A similarity between both of the conditions was seemingly more random occurrence of non-static movements (walking, crawling) along students' solution paths. For example, in problem 1, non-static movements do not occur more frequently near the start state or a correct/incorrect solution submission for either condition. As shown below in Figure 7.7

and Figure 7.8 non-static behaviors in both conditions occur a similar frequencies at the beginning, middle, and end of students' solution paths.

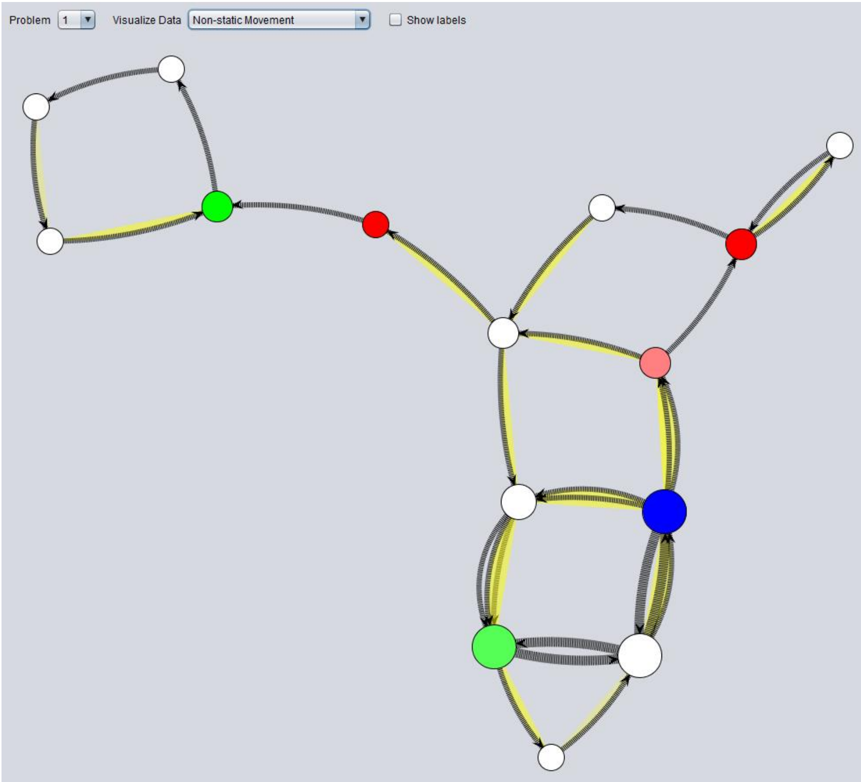

Figure 7.7 Aggregate graph for problem 1 modeling solution paths of students in the ABSTRACT condition with non-static actions highlighted in yellow.

This trend continues even when looking at a particular subset of non-static behaviors, such as walking around to different areas of the Cartesian plane. Since students in the ACTION condition performed this particular behavior much more frequently than their counterparts in the ABSTRACT condition, the aggregate graphs for problem 1 were also analyzed while highlighting only at occurrences of walking around the Cartesian plane. Figure 7.9 and Figure 7.10 show no visible pattern regarding what part of the problem-solving process students were more likely to walk around.

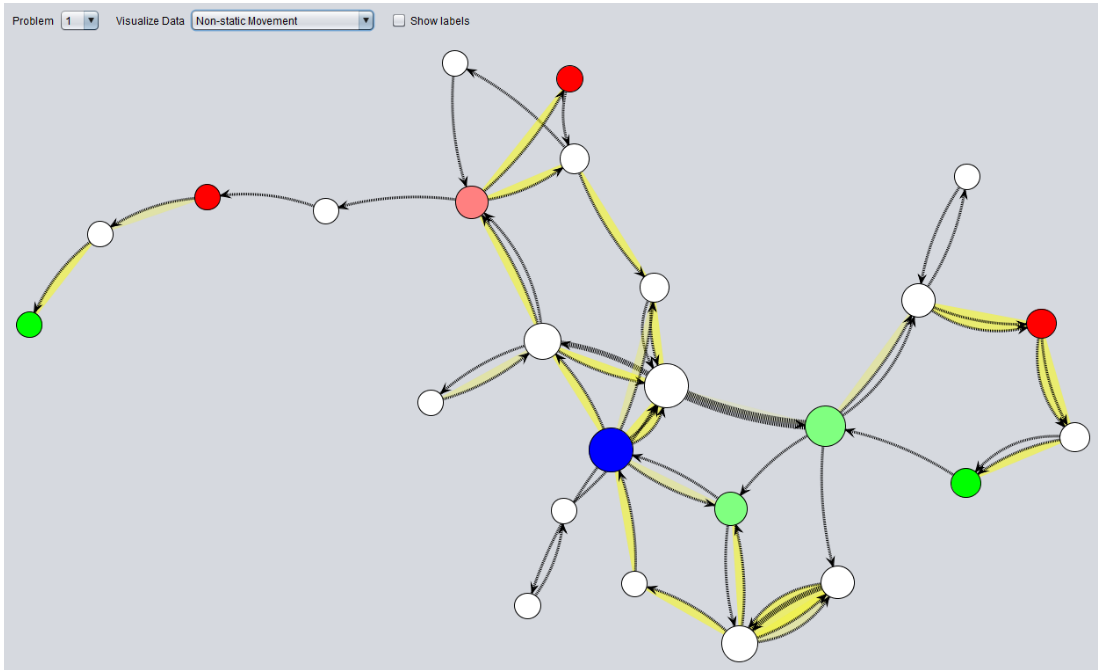

Figure 7.8 Aggregate graph for problem 1 modeling solution paths of students in the ACTION condition with non-static actions highlighted in yellow.

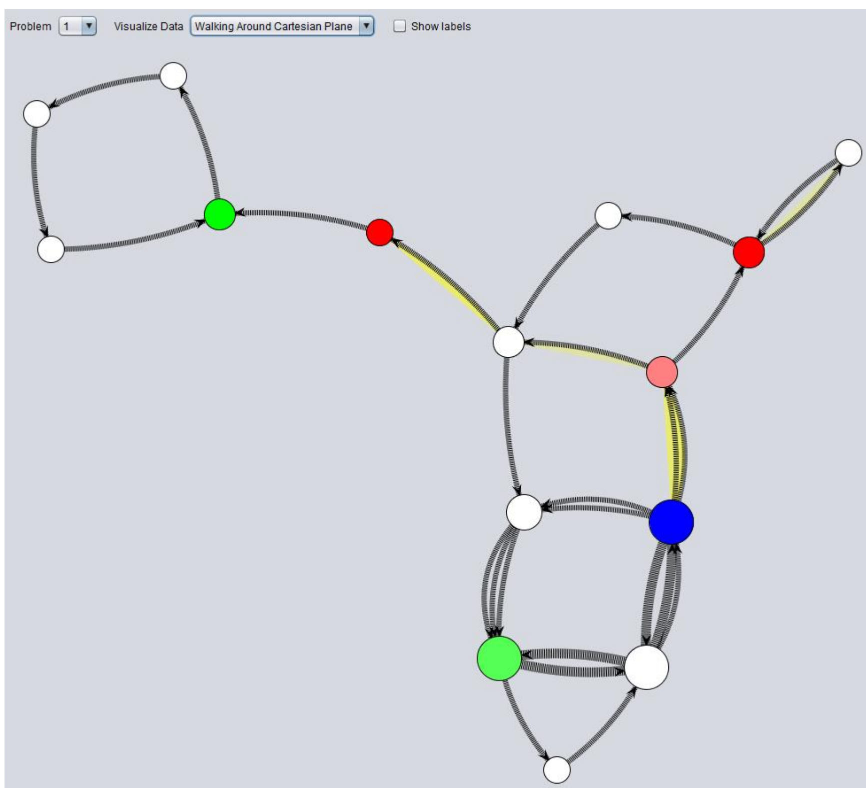

Figure 7.9 Aggregate graph for problem 1 modeling solution paths of students in the ABSTRACT condition with instances of walking around the Cartesian plane highlighted in yellow.

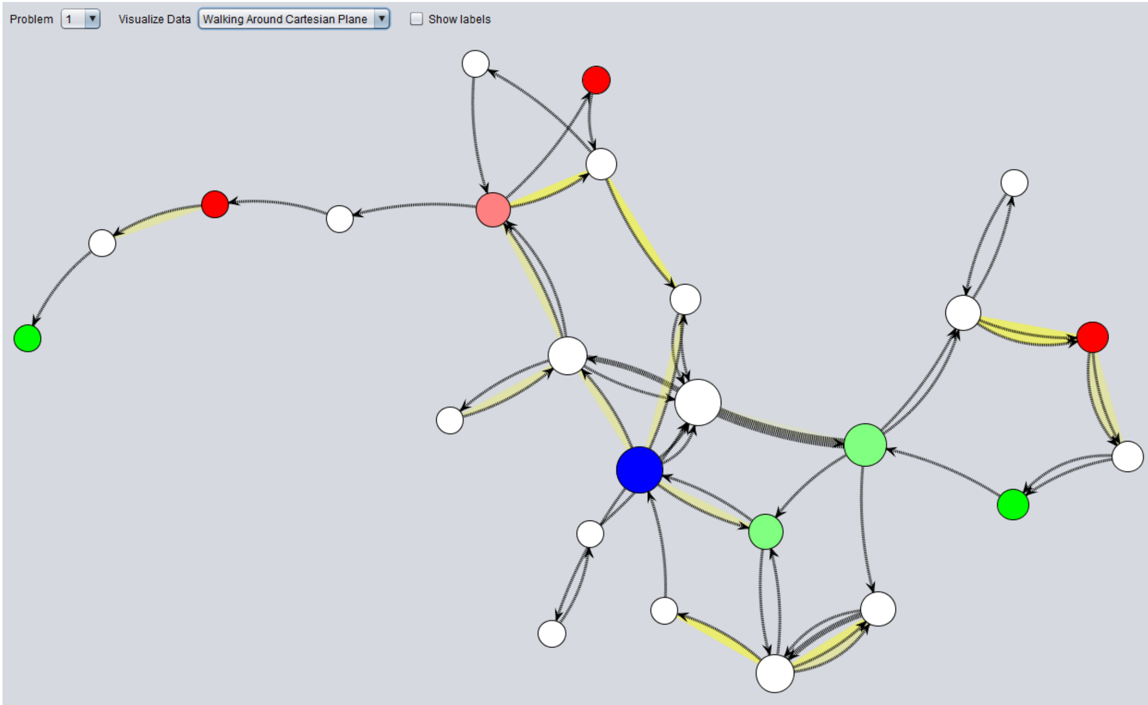

Figure 7.10 Aggregate graph for problem 1 modeling solution paths of students in the ACTION condition with instances of walking around the Cartesian plane highlighted in yellow.

Summary of Process Analysis Results

There were both similarities and differences regarding where along their solution paths students in the ABSTRACT and ACTION conditions performed different kinds of physical gestures and behaviors. Similarities include the seemingly random nature of non-static movements in both conditions. Differences include the trend of bending or kneeling near the robot in steps directly preceding the submission of a solution that was seen only by students in the ABSTRACT condition.

CHAPTER 8

DISCUSSION

The three main sections of Chapter 8 discuss the results of the three hypotheses which were outlined in Chapter 7.

8.1 Discussion of H1 Results

This section will discuss the findings related to the accuracy of solutions submitted by participants in the ABSTRACT prompt pool versus the accuracy of solutions submitted by participants in the ACTION prompt pool.

Increased Performance Accuracy for Subjects in ABSTRACT Condition during Pre/Post-Test Assessments

Participants who encountered prompts from the ABSTRACT condition showed more significant improvement of scores between pre-test and post-test assessments. This shows that there is not necessarily a correlation between being prompted to explicitly move and gesture in a tangible learning environment by prompts delivered through a teachable robotic agent and short-term learning gains. There are a few possible explanations for this occurrence. First, prior research has demonstrated a connection between gesturing and other types of physical behaviors and learning. The fact that increased performance accuracy was not observed during this study might indicate that the benefits from using explicit prompts for action in a TLE are more observable when testing for long-term retention of knowledge. An additional follow-up with students could provide more insight into the full impact of the ACTION prompts on the students who encountered them. Additionally, it is interesting to note that during a survey of students' perceptions administered at the end of each session, students in the ABSTRACT and ACTION conditions perceived the prompts as equally helpful, as shown in Table 8.1 Based on this information, it may be worth further investigation to see as to whether or not the ACTION prompts are benefiting students in a way not measured by this study.

Condition	**Average Response**
ABSTRACT	4.75
ACTION	4.75

Table 8.1 The average of students' responses when asked to rate on a scale of 1-Strongly Disagree to 5-Strongly Agree, whether or not they agree with the statement "Answering Quinn's questions about geometry helped me figure out how to plot points."

8.2 Discussion of H2 Results

This section will discuss the findings related to the problem solving efficiency of participants in the ABSTRACT prompt pool versus the problem solving efficiency of participants in the ACTION prompt pool.

There were some differences in the performance efficiency of students in the ABSTRACT and ACTION conditions. Students in the ABSTRACT condition took slightly longer to solve various geometry problems using TAG than their peers in the ACTION condition. The fact that students in the ACTION condition were able to solve problems more quickly while using TAG, despite the additional time taken for the agent to deliver their prompts and the extra time taken to physically respond to the agent's remarks would suggest if the prompts were not beneficial, students in the ACTION condition should actually be taking longer to solve geometry problems using TAG. Since this is not the case, these results could indicate that the actions and gestures students were prompted to perform in the ACTION condition helped students solve the problems they were working on. Whether or not the benefits of motioning and gesturing during problem solving transfer to a more abstract problem-solving activity will be discussed below.

Students in the ABSTRACT condition increased their performance efficiency from the pre-test assessment to the post-test assessment while students in the ACTION condition reduced their performance efficiency from the pre-test assessment to the post-test assessment. These results could be the result of the differences between the prior knowledge of students in each condition. Since students in the ABSTRACT pool came in with a higher prior knowledge of the domain content (as evidenced by their higher pre-test scores) their time using TAG might have served more as a refresher activity than a learning activity, allowing them to more easily increase their performance efficiency on the post-test assessment. Additionally, because of the prompts that students in the ACTION condition received, students in this condition might have taken more time to complete the post-test assessment because they were reflecting back to the physical embodiment of the concepts they experienced during TAG usage and using this experience to help them get through problems on the assessment. Also, students in the ACTION condition might have taken less time to complete the pre-test simply because they were unfamiliar with the content. Students were instructed not to guess on problems during the pre-test or post-test. Because students in the ACTION condition appeared to have less prior knowledge about the domain content, it is possible that they skipped one or many problems on the pre-test that they then attempted to work through during the post-test using the knowledge and skills they gained from their interaction with the TAG system.

8.3 Discussion of H3 Results

This section will discuss the findings related to the behavior models generated by participants in the ABSTRACT prompt pool versus the behavior models generated by participants in the ACTION prompt pool.

Types of Physical Behaviors Observed

There are a wide variety of gestures and other physical behaviors students have the freedom to perform while using the TAG system. Through video analysis, the different behaviors exhibited by students in both the ABSTRACT and ACTION prompt pools were noted and added to the original log files as annotations.

It was observed through video analysis that students in the ABSTRACT condition exhibited different types of behaviors than their peers in the ACTION condition. Students in the ABSTRACT condition tended to remain physically closer to the ground. Because these students were not being explicitly prompted to walk or move very much around the Cartesian plane, it is possible that they chose to stay close to the robot since proximity to the robot is necessary for the click action that allows students to issue one of three commands to the robot. Since students in the ACTION condition were frequently prompted to walk or move around the Cartesian plane, it is possible that they avoided being on the ground because the prompts they were receiving would not allow them to stay there for an extended period of time.

In addition to the general location associated with behaviors, students in the ACTION condition also exhibited a noticeably higher number of static gestures, such as pointing. It is likely that this a direct results of these students being explicitly prompted to point at different elements of the problem space through the prompts they received. Students in the ABSTRACT condition were never explicitly asked to point or gesture in any way, and therefore exhibited these types of behaviors at a much lower rate.

Frequency of Physical Behaviors Observed

There are many opportunities to exhibit different physical behaviors while they are using the TAG system. Through video analysis, the occurrence of behaviors exhibited by students in both the ABSTRACT and ACTION prompt pools was noted and added to the original log files as annotations. The largest difference between the frequencies of different behaviors observed was the amount of walking around the tangible problem space that was done by students in the ACTION condition versus that done by students in the ABSTRACT condition. It is likely that students in the ACTION condition walked around the tangible problem space more frequently because they were being prompted specifically to do so, while students in the ABSTRACT condition were never prompted to do this. However, in the process of answering Quinn’s questions students in the ABSTRACT condition did still show some occurrences of walking around the problem space. There was also a slightly higher frequency of pointing actions performed in the ACITON condition than there was in the ABSTRACT condition. Again, it is possible that pointing gestures are not intuitive to students in this type of learning environment and, if they are found to be beneficial gestures for learning, are a type of action that must be prompted for.

Summary

The major difference between the types of behaviors performed by students in the two conditions was that students in the ABSTRACT condition favored static gestures and behaviors while students in the ACTION condition favored non-static movements. This might indicate that non-static gestures are less intuitive in a tangible learning environment. Although both groups demonstrated a wide array of behaviors, the ACTION condition moved more within the tangible problem space overall, possibly because the robot was prompting them to do so every two minutes.

8.4 Discussion of Process Analysis

This section will discuss the results of process analysis performed using the modeling and analysis tool described in Chapter 5.

There were noticeable differences between the two conditions in where different behaviors occurred along students' solution paths. In the ABSTRACT condition, students were more likely to perform static behaviors in close proximity to the robot immediately before submitting a solution to the system. Students in the ABSTRACT condition may have remained close to the robot because it allowed them to initiate interactions with the robot more quickly, and thus, in their opinion, move through problems more quickly. Additionally, there might be some element of the wording ABSTRACT prompts that makes students feel the need to stay closer to Quinn. For example, since students in this condition are asked abstract questions which the majority of students answered by talking out loud to Quinn, they might have stayed in closer proximity to Quinn so that it could hear their answers better.

Additionally, some of the behaviors and gestures encouraged through the prompts in the ACTION condition did not seem to correlate to any particular state of the problem-solving process. Specifically, prompting students to walk around the tangible problem space did not seem to lead students towards a correct solution state or help students generate more optimal types of solution models. This might indicate that this type of behavior is not the most beneficial action for learning in this type of learning environment. Testing the effects of other types of behaviors and gestures in this type of learning environment could help to determine if this is the case.

8.5 Conclusion

The results from this study comparing the use of ABSTRACT and ACTION prompts with a TLE were mixed. Overall, the ACTION prompts did not have a strong effect on the learning performance of students. The ACTION prompts did not help students to perform better on their peers during TAG usage or pre/post-test assessments. There were some indications that the ACTION prompts may have helped students work through problems more quickly during TAG usage, but this increase in performance efficiency did not transfer to the abstract assessments students received following their experience tutoring Quinn.

However, in regards to whether or not the ACTION prompts could be used to enhance the affordances of a TLE, the different types and frequencies of behaviors exhibited by students in the ABSTRACT and ACTION conditions indicate that prompts which include explicit action verbs can be used to influence student behavior in this type of learning environment. If future research was to identify a set of optimal student behavior from this type of system, prompts such as those proposed in this work could be used to encourage students' use of those behaviors in a TLE.

Overall, the results from this master's thesis indicate that the design of a TLE utilizing a teachable agent framework should carefully consider the content of prompt s delivered to students. Additional work should be done to determine how varying the types of prompts encountered in this type of learning environment can be used to increase learning and physical engagement with the learning environment. Learning benefits to students may not have been accurately captured in the small scope of this study and could be more evident through longer exposure to this type of learning environment or testing of long-term retention of content. How students respond to additional action verbs could also be studied further to allow researchers and educators to design systems that successfully encourage students to exhibit movements and gestures that will have the strongest impact on learning. Similar studies in this type of learning environment could also be done in other domains to see if the results in a relatively abstract subject-area such as math are similar to less abstract subject-areas.

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APPENDIX A

COGNITIVE PROMPT SURVEY

SUBJECT ID ____________________ DATE ____________________

For each question, circle the number that you feel best fits with what you think:

1. **I liked when Quinn asked me questions about geometry.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

2. **Quinn's questions about geometry were confusing and didn't make sense to me.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

3. **I had to move around a lot to answer Quinn's questions about geometry.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

4. **Quinn learns a lot when I talk about different things on the Cartesian plane.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

5. **Quinn learns a lot when I move around and show it different things on the Cartesian plane.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

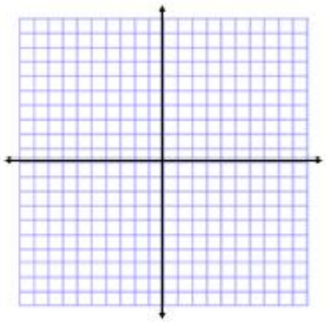
6. **Answering Quinn's questions about geometry helped me figure out how to plot points.**

1	2	3	4	5
Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*

APPENDIX B

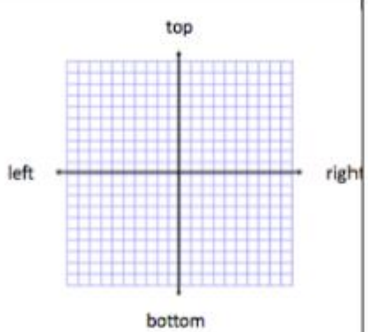
PRE/POST-TEST ASSESSMENT

Subject ID ____________________ **Date** ___________________ **Test: (PRE / POST)**



1. In the picture below, **circle** and **label**:
   - the x-axis
   - the y-axis
   - the origin

2. With the point (3, 6), the **x-coordinate** is ________
3. With the point (-3, -1), the **y-coordinate** is ________
4. With the point (-2, 4), the **x-coordinate** is ________
5. With the point (5, -9), the **y-coordinate** is ________



For the next set of questions, assume you have the axis shown on the left, and you are standing at the point (0,0) facing the label "**top**". Circle the best answer for each question.

6. When plotting the point (3, 6), for the "3" coordinate, you have to move: left/right or top/bottom
7. When plotting the point (1, 8), for the "8" coordinate you have to move: left/right or top/bottom
8. When plotting the point (-2, -3), for the "-2" coordinate you have to move: left/right or top/bottom
9. When plotting the point (-4, -5), for the "-5" coordinate, you have to move: left/right or top/bottom