

Analyzing the Effect of an 'Open Learner Model' Represented Through a Feedback System  
in a Teachable Agent System

by

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## ABSTRACT

For this master's thesis, an open learner model is integrated with Quinn, a teachable robotic agent developed at Arizona State University. This system is represented as a feedback system, which aims to improve a student's understanding of a subject. It also helps to understand the effect of the learner model when it is represented by performance of the teachable agent. The feedback system represents performance of the teachable agent, and not of a student. Data in the feedback system is thus updated according to a student's understanding of the subject. This provides students an opportunity to enhance their understanding of a subject by analyzing their performance. To test the effectiveness of the feedback system, student understanding in two different conditions is analyzed. In the first condition a feedback report is not provided to the students, while in the second condition the feedback report is provided in the form of the agent's performance.

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## CHAPTER 1

### INTRODUCTION

Teachable agents provide an educational technology where students assume the role of a “Tutor”. The tutor teaches a subject to the agent and learns in the process of teaching [1]. This agent presents the concept of providing an effective learning environment through a system where the act of teaching adds to one’s own learning [16]. This opportunity to teach improves the effectiveness of learning by making students feel responsible for their agent, and motivates them to try harder to learn [15]. Teachable agents also allow students to analyze their misconceptions and expand their understanding of the domain [1] [15].

Studies show that during the teaching process, reflecting on the interaction between the tutor and the agent helps the tutor to prepare better for future learning sessions [21]. The interaction between a tutor and the agent represents the tutor’s understanding and misconception. The model that holds this information is known as the learner model. When this model is made accessible to the tutor or the student, it is known as an open learner model.

One way to augment the effects of a teachable agent in terms of increasing learning efficiency is through an open learner model. To assist students in comprehending their learning, research is done to render a learner model for students. The learner model provides a source of information to the students, which helps them to analyze their current understanding of the domain.

This research aims to analyze the effect of integrating an open learner model with the teachable robotic agent Quinn. It aims to determine the improvement in the effectiveness of the learner model when it is represented as the teachable agent’s performance rather than the student’s performance. The number of correct and incorrect attempts and the amount of time taken by a student with Quinn during a session measure the student’s performance. The system has



predefined knowledge of the domain, and it pretends to learn from the student. The performance report is based on a student's interaction with the agent for solving a problem and does not include any participation from the agent. The open learner model is represented in the form of a feedback system to the student. It displays the information about performance, misconception, and knowledge. To illustrate the teachable agent's paradigm and encourage students to perform better for their agent, the feedback system presents the agent's report rather than the student's report. The agent's report represents the student's ability as a tutor.

To maximize the potential of improving learning efficiency through the open learner model, I include a feedback report and a learner report that represents a feedback system for students. In my previous work I developed a prompt delivery system for Quinn. The prompt was designed based on the common misconception faced by students while solving the problems with Quinn. The data specific to a problem type was analyzed by examining the results of previous studies and problems faced by students. This common misconception data is used for the learner and feedback reports implemented for this research. The learner report provides students an opportunity to enhance their performance by understanding the domain even before the problem is presented to the students. The feedback report helps students understand their performance and benefit from it by preparing for future problems.

## CHAPTER 2

### BACKGROUND AND THEORY

#### **2.1 Teachable Agent**

A teachable agent, where students teach an agent and learn from that collaboration, has been acknowledged to foster the benefits of learning by teaching [9]. They have been used as a tool to help students learn and acquire a deeper understanding of the subject [20]. The learning by teaching method also provides an enhanced grasp of the material with increased motivation and enjoyment [15,18,19]. The learning by teaching method affects important aspects of learning interactions like organizing the idea better by structuring domain knowledge [23, 25], taking responsibility of their agent and deciding which content is more relevant [25], and reflecting on the interaction between the agent and the student to prepare better for future learning sessions [21,22].

Various systems have been developed in the past, where students teach an agent and learn from that interaction. The three factors that play a primary role in characterizing the teaching agent systems are [13]: 1) Explicit teaching: A system where the teaching task is made explicit. In this system either the agent has a limited knowledge of what it has been taught by the tutor, or has the internal knowledge of the domain and it pretends to learn from the tutor. 2) Shared representation: The information is stored about what the tutor has taught the agent. The information is represented either explicitly by making it visible to the tutor or implicitly by storing it into the internal representation without making it available to the tutor. 3) Shared responsibility: The teaching responsibility is shared between the tutor and the agent. The aim is to make the tutor and the agent learn through mutual interaction.

The existing systems have identified that teachable agents lead to active learning where students act as tutors and assist in their own education [16]. Students, represented as a tutor, get a

chance to analyze how the teachable agent has applied the learning to solve a problem. This provides students an opportunity to explore their own understanding [13]. Active learning is a concept wherein students are involved in discussion and problem-solving, and not just listening to a tutor. It provides a deeper understanding of the domain [16].

### **Examples of Teachable Agents**

Betty's brain [13] is a teachable agent developed to promote learning in the science domain. This teachable agent combines learning by teaching with feedback to encourage a better understanding of the domain [13]. Betty's brain is an open-ended learning environment, providing students the task of modeling science phenomena. This system employs the concept of explicit teaching and shared representation. Students learn from the provided material. Then the students represent their understanding in a map format and use quizzes to check Betty's performance. This allows students to utilize their cognitive skills and develop their ability to regulate a future learning process. Studies of this system demonstrate that learning-by-teaching helps students develop better learning strategies [13]. Betty's brain modified its design to address students' difficulties and introduced feedback delivery. The feedback delivery is based on: 1) Principles of goal alignment, which recommend techniques to students and explain the ways to employ them. 2) Context relevancy that focuses on a learner's current situation. 3) Cognitive support that provides support to all the required skills of the student.

Simstudent [26], a synthetic peer learner, is also a teachable agent that models human learning. The system is embedded into an online environment termed as an artificial peer-learning environment using Simstudent (APLUS) where students learn algebra equations by the teachable agent's paradigm. The system is integrated with some background knowledge of the domain. To model human learning, the background knowledge is modified to identify the difference in the learner's ability during the tutor's learning process [26]. This utilizes the concept of explicit teaching and shared responsibility. Further work on Simstudent was to create a cognitive model

to replicate a tutor's performance. The system observes the tutor's problem-solving pattern and predicts performance on novel problems, based on the cognitive model created for the tutor [27].

Math concept learning system (MCLS) [24] is a teachable agent developed for solving linear equations in math. The system has inbuilt knowledge of the structure of linear equations, and it employs the concept of explicit teaching. Students teach the system by posing an example solution, then the system uses a machine-learning algorithm, ID3, on the example to learn problem-solving techniques. This system uses the shared representation teaching system and provides a knowledge representation that can be viewed by the students [24].

Mathematics computer game for children is a teachable agent designed to promote fundamental reasoning and other cognitive activities [17]. This system demonstrates the effectiveness of educational games for developing cognitive skills by employing the concept of explicit teaching. The game prompts students to choose a card representing a number and place it on a game board representing a number. The challenge is to make the best choices considering the card and the game board. The choices give the ability to reason over and invent strategies, which motivates fundamental reasoning and productive choice among students [17].

To extend previous work on enhancing the effect of a teachable agent by creating a learner model for the tutor, my research focuses on maximizing the aspect of learning by teaching, by representing the information of the learner through an open learner model. The open learner model captures the learner's understanding of the domain and represents it on various factors. For my thesis, I sought to create a feedback system delivered through a teachable agent as an externalized learner model, which will help students analyze their learning process with a detailed overview of their knowledge, understanding, and misconceptions, and can also be used to recommend what areas need more understanding and improvement.

## 2.2 Open Learner Model

The open learner model holds information about a learner and adapts the educational interaction based on the learner's needs [3]. The model represents the understanding, knowledge, misconceptions, and difficulties of the learner and updates this information in the system according to the current performance of the learner [2]. Making the learner model accessible to students also has educational benefits. It raises learners' awareness about their learning process and helps them identify their difficulties.

There are four main types of open learner models: 1) Inspectable, where the learner model is available for viewing only to a student; 2) Cooperative, where the modeling task is shared between the student and the system; 3) Editable, where students have the option to alter the content of the learner model; 4) Negotiated, where the model is represented as a result of a discussion between the student and the system [2,5].

The representation of a learner model can be simple or complex, and varies based on the portrayal of the model. A simple representation of a learner model displays a student's level of achievement commonly in the form of skill meters [4]. This provides students information about their problems and indicates the level to which the student has mastered the material. Although most systems display the learner model in the same format, learners may want to access the model in other ways [6]. One example of providing the learner model in a different format is the Japanese particle learning environment [3]. This system displays the learner model in a tabular format showing overall performance and correct versus incorrect attempts. The proficiency level is displayed graphically and learners can either access both the representation together or choose the one they prefer [3].

The learner model, which allows students to discuss the content, is termed as a *negotiated*

learner model. The negotiated learner model may achieve more accurate information, since the learner can provide information that might be difficult for the system to obtain [5]. The learner has control over the negotiation process and it can be started by either the learner or the system. In cases where the learner and the system do not agree on the content, the learner model might infer inconsistent beliefs [2,5].

### **2.3 Feedback System**

To maximize the effects of learning by teaching, via presenting the information of the learner through an inspectable learner model, I have implemented a feedback system in the teachable agent, Quinn. This system represents the student's learning curve in terms of understanding, misconceptions, and difficulties. The feedback system I have designed highlights student achievements while also analyzing shortcomings by detailing the mistakes. The system also provides the best solution to avoid similar mistakes in the future, which raises learner's awareness and reasoning ability.

The feedback report is implemented on tangible activities for geometry (TAG) to determine the areas of improvement in a student's learning and understanding. Two types of reports are displayed. The first report is a learner model that represents the misconceptions of previous learners on a problem type. The aim of this report is to inform students about the misconceptions of previous learners before they attempt to solve a problem. This can reduce the incorrect attempts and make students comprehend the problem more accurately.

The second report is the feedback report, which is displayed after a student attempts a problem correctly. This is a detailed report of a student's performance as a tutor and represents the agent's feedback as a learner. The report will be displayed only after a student manages to reach the correct solution. Explicating on the type of problem the report represents the performance, misconceptions, incorrect attempts and accuracy level. It also aims to improve students

understanding and prepare better for future learning.

The goal of the research is to determine the motivational use of the feedback report in Quinn by the students during the study, and its effect in enhancing the knowledge, understanding, and learning of the student. The learner report is researched to determine the improvement in performance of students based on the judgment of the presented misconceptions of previous attempts. The feedback report is researched to determine the enhancement in the learning curve and understanding of the domain of the student and the sense of responsibility experienced by the student as the report is presented as Quinn's performance rather than the student's performance.

## CHAPTER 3

### SYSTEM

#### **3.1 Tangible Activities for Geometry**

The tangible activities for geometry (TAG) system that I am using for my research is a teachable agent platform developed at Arizona State University. It implements the teachable agent's paradigm on a virtual environment and a physical environment [11]. This system aims to help middle school students learn geometry, where the students teach the robot the geometry concepts and learn while teaching [1].

#### **Physical Environment –**

The physical environment of TAG is comprised of three main components [1] [11]:

1. The problem space: This is a web page projected on a physical space. The web page is powered by the GeoGebra (Geometry application) applet that displays a Cartesian plane, as shown in Figure 3.1. The Cartesian plane displays points and lines and gives students the ability to walk through the problem space and interact with the robotic agent [1,11].



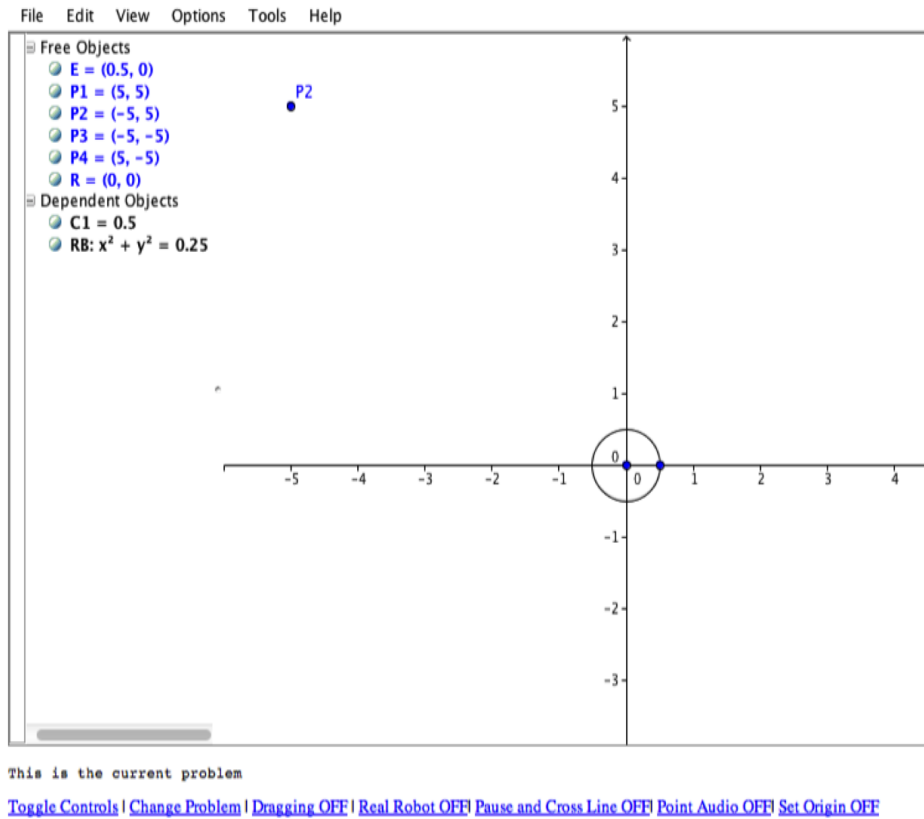
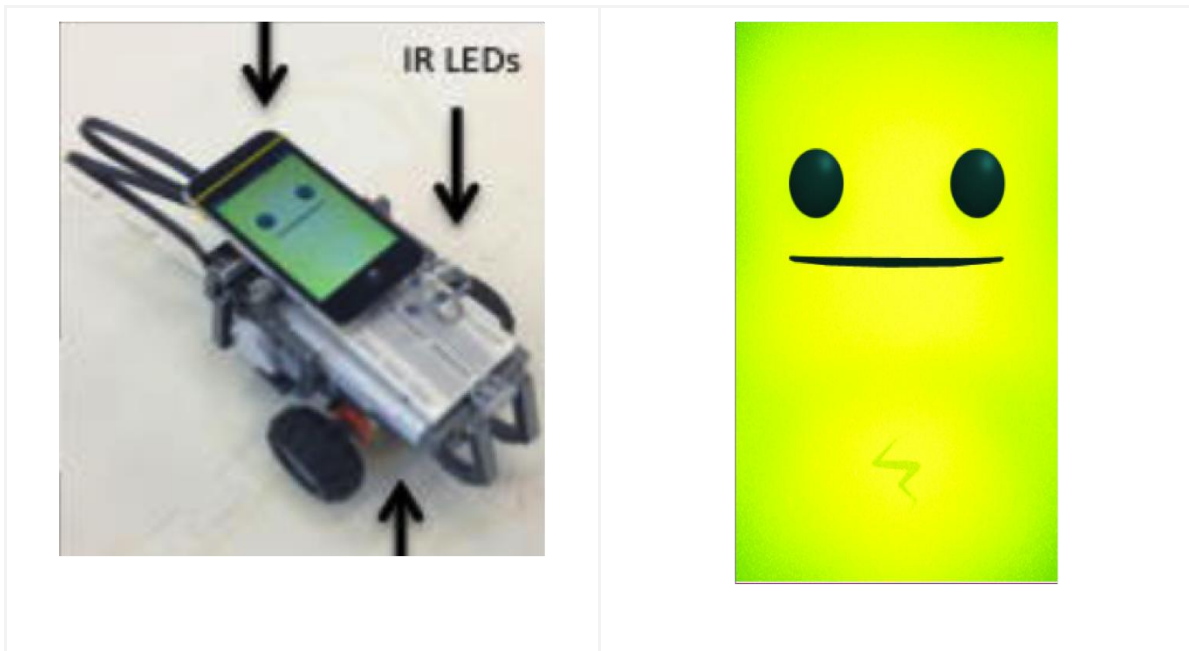


Figure 3.1: The problem space in TAG

2. Quinn (Teachable Robotic Agent): This is a LEGO mind storms NXT 2.0 robot. It is built as a three-wheeled vehicle and has an iPod mounted on its robotic body. This helps in communicating with students as shown in Figure 3.2. Students are given a problem and Quinn is provided the step-by-step instructions for the correct solution. The iPod's interface consists of a clickable face that triggers the list of actions on the mobile interface when the student touches the robot's face [1] [11]. The robot's face is also used to display several text messages, in the form of prompts, and play audio files.



*Figure 3.2: Teachable robotic agent Quinn*

3. TAG (Mobile Interface): The mobile interface is an iPod touch, which displays the problem to the student. It provides them with a list of actions as shown in Figure 3.3. The set of actions displayed here are—Move: For moving the robot to the input point value; Turn: For turning the robot to the input angle value; Plot Point: For letting the system capture the present coordinate point (location) of the robot. All the actions take input from the student and the robotic agent in the problem space executes the selected actions. It also provides the student an option to check their solution and display the result.

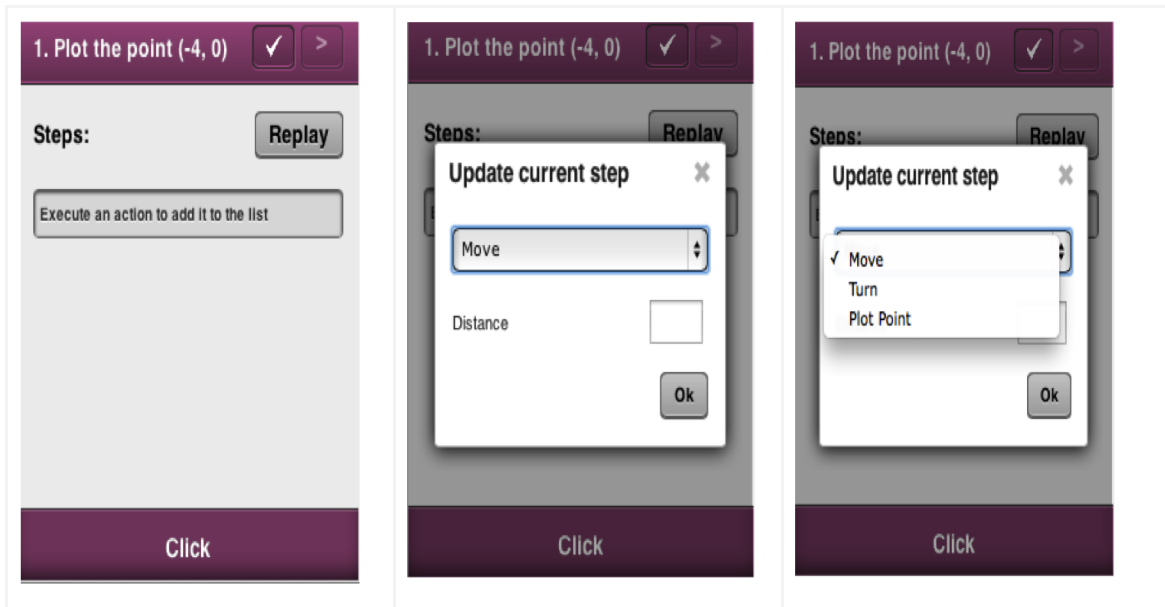


Figure 3.3: The mobile interface in TAG

### Virtual Environment –

The virtual environment is comprised of three components: Cartesian plane, Quinn, and mobile interface as a web page, as shown in Figure 3.4. The Cartesian plane displays a visual point that replaces the robot and the point conceive the action entered by the student through the mobile interface. The mobile interface and Quinn are both represented by web pages and hold the same action list and functions as in the physical environment.

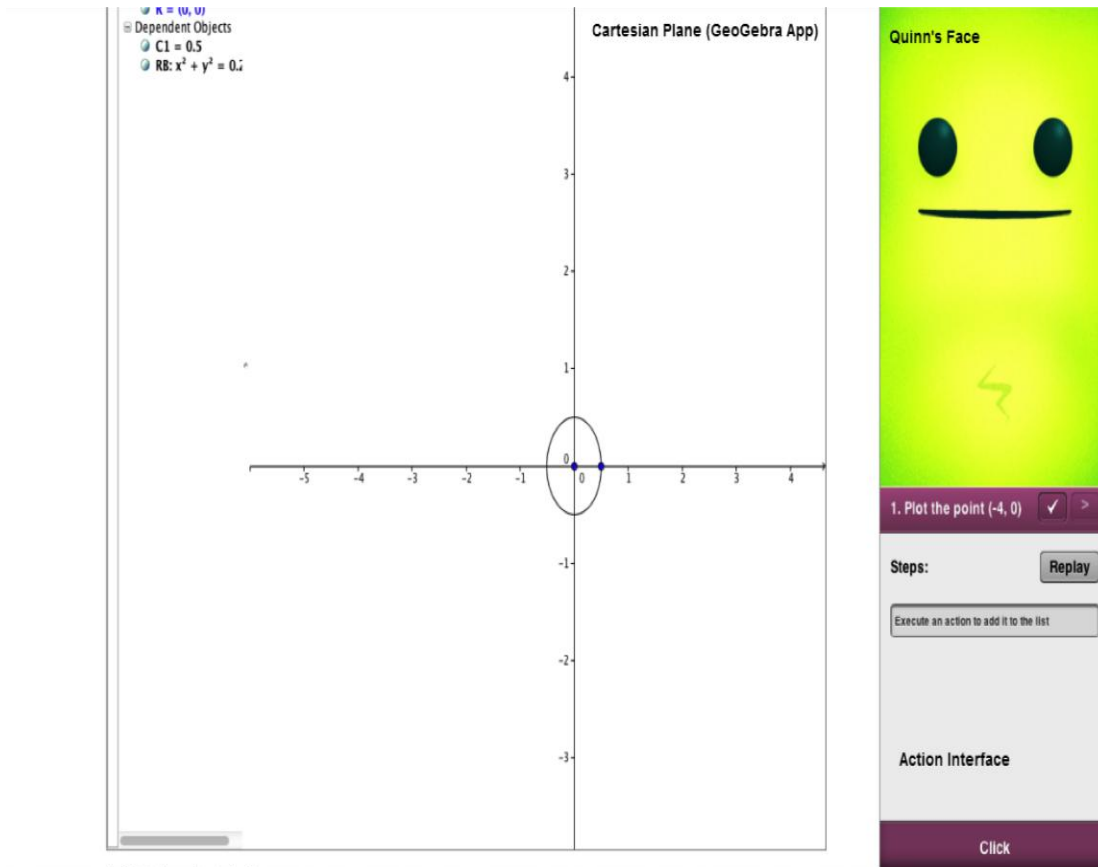


Figure 3.4: Virtual environment in TAG

### Solving a Problem –

The problem is showed to the student through the mobile interface. The robot is initially placed at the origin of the Cartesian plane. The student starts directing Quinn on how to solve the problem by executing the actions step by step through the mobile interface. One action is executed at a time and the student enters the input for each action. To check the solution, the student will have to plot the point by selecting the option from the action list, and then the solution can be checked through the check button. The result is displayed as an image (cross sign for incorrect and check sign for correct) in the mobile interface and as a voice and text message in the Quinn's interface. Table 3.1 displays the set of steps required to guide Quinn through a given problem.

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: Example of problem given to students*

**Feedback Mechanism –**

Previous works on the feedback mechanism in TAG were not incorporating an intelligent learning environment. The feedback information only displayed the direct result without holding any information of the student or the learner. It doesn't represent the learning curve of the student, and hence does not necessarily encourage students to learn from their mistakes and improve their learning for future problems. To address this, a feedback system is developed in TAG, representing an open learner model to help students understand their learning.

***System Correctness Feedback –***

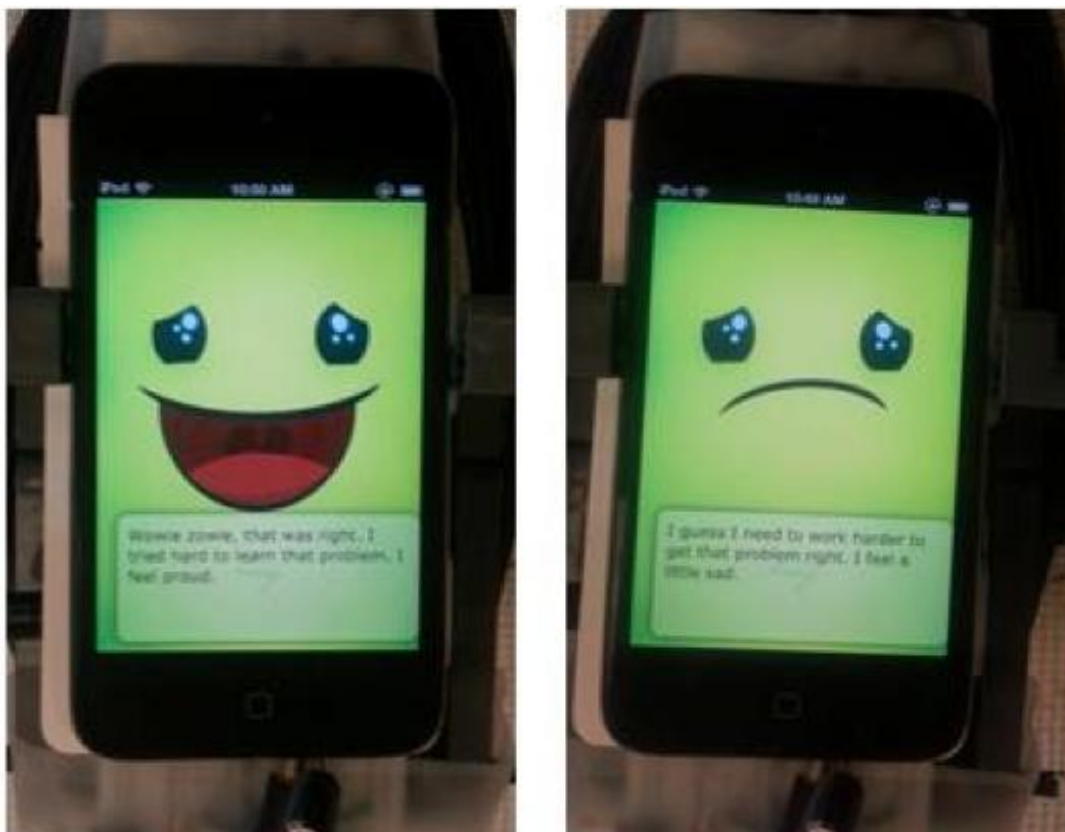
Students have the option to check their solution when they believe they have guided Quinn to the correct point. In the case of a correct answer, students see a check mark on the mobile interface with Quinn's happy face along with an attribution message and audio of a drum roll. In the case of an incorrect answer, students see a red 'X' mark on the mobile interface with Quinn's sad face along with an attribution message and audio of a buzzer. Students cannot move to the next problem until they get the correct answer.

***Attribution Message –***

The attribution messages are divided into two pools based on the correct and incorrect result and each pool has eight different messages. They are delivered to the students after a solution check through voice and text in the mobile interface. Quinn randomly chooses an attribution message from one of the two pools. Table 3.2 shows an example of an attribution message for correct and incorrect solutions. Figure 3.5 also displays how the attribution message is represented to the student through Quinn.

<b>Action</b>	<b>Attribution Message</b>
Correct Solution	That was right. Holy cow, you worked hard at teaching me that problem. I feel grateful.
Incorrect Solution	Oh boy. I got that wrong because I did not try hard to learn. I feel guilty.

*Table 3.2: Example of attribution message*



*Figure 3.5: Photo of attribution messages delivered to users*

### ***Cognitive and Action Prompts –***

From my previous work in TAG, I implemented action prompts to encourage students to incorporate the mathematical concepts they were required to learn to guide Quinn to a solution. When students guide Quinn to the correct solution by various actions, the system and Quinn communicate to the students through audio or visual means. The mechanism to guide the student to the correct solution is termed action prompts. The action prompts do not directly guide the student to the correct solution but prompt them in an indirect way to think in the correct direction if they are on a wrong track.

When students believe they have guided Quinn to the correct point, they have the option to check

their solution. To analyze and represent the result I implemented cognitive prompts. The cognitive prompts are designed to display the concept related to the result, to encourage students to analyze the mistake in the case of an incorrect solution or to incorporate the concept in case of a correct solution. For a correct solution, students see a cognitive prompt based on a concept related to the correct solution and then the students can move to the next problem. In the case of an incorrect answer, students see a cognitive prompt specifying indirectly the type of mistake the student made. Table 3.3 shows an example of action prompts for a student's step on a problem and a cognitive prompt after checking the solution.

<b>Problem</b>	<b>Student's Input</b>	<b>Prompt</b>
(4, 0)	-4 on x-axis	"If the x-coordinate is positive then don't I have to move towards the right side of the x-axis?" (Action Prompt)
(4, 0)	(-4,0)	"I want to understand positive and negative values better...could you look at the left side of the x-axis and see if x is positive or negative there?" (Cognitive Prompt)

*Table 3.3: Example of action and cognitive prompt*

The current feedback mechanism in TAG is based on a single problem, one step at a time, and doesn't keep track of whether students are developing knowledge, difficulties, and misconceptions, considering all problems and all efforts made by the student. The attribution messages and prompts display the information in a direct or indirect way without representing the learning curve of the student or the system. This doesn't provide students enough information on their progress and students might tend to make the same mistake repetitively.



## CHAPTER 4

### FEEDBACK REPORT

To address the limitations of the previous feedback mechanism and to enhance the effect of the feedback system in a teachable agent, for this master's thesis I have implemented a feedback system in TAG representing an open learner model to help students better understand their learning. The feedback system is a model about knowledge, difficulties, and misconceptions of the student [2], but it is represented as Quinn's performance and the student's ability as a teacher. The feedback is given once for each problem, implementing the concept of the outer loop [28], and once based on each step taken by the student to assess student's learning progress, implementing the concept of the inner loop [28]. As the students move forward with each problem, the information and data in the feedback system are updated based on their understanding to reflect their current belief and overall performance [28]. The feedback system then continues to adapt, as appropriate for the student, which offers an intelligent learning environment (ILE) to students [2].

Providing students with the feedback system based on Quinn's performance offers a source of information about their learning curve, which is otherwise unavailable, and encourages them to reflect on their beliefs and on the learning process [3]. Previous studies have suggested that offering a choice of views on the learner model may also be beneficial [7, 8].

The current feedback report is designed to align with targeting common misconceptions students face while solving a problem particular to a quadrant in the Cartesian plane. The misconceptions displayed as part of the feedback report are designed to aim the ten unique corresponding misconceptions, which were identified during the analysis of results from a previous study with the TAG system. Table 4.1 shows the identified misconceptions with their explanation and the type of message displayed in the report for addressing the mistake.

<b>Mistake</b>	<b>Explanation</b>	<b>Message</b>
No move on positive x-axis	When the problem has point on positive X axis and Quinn doesn't make a move	I did not make any move on the positive side of the X-axis.
No move on negative x-axis	When the problem has point on negative X axis and Quinn doesn't make a move	I did not make any move on the negative side of the X-axis.
No move on positive y-axis	When the problem has point on positive Y axis and Quinn doesn't make a move	I did not make any move on the positive side of the Y-axis.
No move on negative y-axis	When the problem has point on negative Y axis and Quinn doesn't make a move	I did not make any move on the negative side of the Y-axis.
Plot point	When Quinn forgets to plot a point before checking a solution	Oh no! I forgot to plot the point, before checking my solution.
Miscalculate sign of X axis	When Quinn moves to the opposite side of the X axis given in the problem	I moved to the wrong side of the X-axis.
Miscalculate sign of Y axis	When Quinn moves to the opposite side of the Y axis given in the problem	I moved to the wrong side of the Y-axis.

Flip points	When Quinn flips the X and Y coordinates	I flipped the X and Y coordinates.
Off by one on X axis	When Quinn miscalculates or starts counting from 1 instead of 0 the point on X axis	I miscalculated the point on X coordinate.
Off by one on Y axis	When Quinn miscalculates or starts counting from 1 instead of 0 the point on Y axis	I miscalculated the point on Y coordinate.

*Table 4.1: Targeted misconceptions displayed in the report*

#### **4.1 Design and Implementation**

The feedback report is designed to be implemented in two different formats: the first format is a learner report, which is delivered before each problem is displayed or when the student moves to a new problem. The goal of the learner report is to prepare students to perform better in the given problem by presenting previous misconceptions faced by Quinn on that problem. The second report is the feedback report, which is presented upon successful completion of each problem. The feedback report displays the detailed performance of Quinn for the solved problem and gives students an opportunity to reinforce and evaluate their understanding of concepts presented in the given problem and improve their learning to better prepare for future problems.

##### **Learner Report**

As the student moves to a new problem, before providing the action interface to the student for solving the problem, the student is provided with the learner report for that problem. This report contains information on how Quinn performed in previous studies on the following problem and

the kind of misconceptions faced by Quinn on previous studies. The information is displayed as a set of prompts targeting the geometry concepts the following problem constitutes. An example of a learner report is shown in Figure 4.1.

Giving students enough information on Quinn's previous performance on the following problem, it encourages students to utilize the information and take advantage of it by reviewing the concepts better before starting to attempt the problem. By explicitly displaying Quinn's previous performance, it will prevent students from making the same mistakes again and will enhance student learning on the following problem, resulting in better performance. The research goal for this report is to analyze the effect of the learner report in improving Quinn's performance for the represented problem.

<p><b>Next Problem :</b> <b>2. Plot the point (-3, 2)</b></p> <p>These are the common mistakes Quinn has previously made for this problem !</p> <ol style="list-style-type: none"><li>1. I did not make any move on the positive side of the Y axis.</li><li>2. I moved to the wrong side of the X axis.</li><li>3. I did not make any move on the negative side of the X axis.</li></ol> <p>Got It!</p>	<p><b>Next Problem :</b> <b>3. Plot the point (1, 3)</b></p> <p>These are the common mistakes Quinn has previously made for this problem !</p> <ol style="list-style-type: none"><li>1. I miscounted the point on X coordinate.</li><li>2. I flipped the X and Y coordinates.</li><li>3. I miscounted the point on Y coordinate.</li></ol> <p>Got It!</p>
--	---

Figure 4.1: Learner reports

## **Feedback Report**

The second report is presented when a student attempts a problem and guides Quinn to the correct solution. This report represents an open learner model and keeps track of Quinn's performance throughout the problem. Explicating on the type of problem, it evaluates the misconceptions, calculates the total time taken to solve the problem, analyzes the accuracy level, and aims to improve student understanding and better prepare for future learning. This is a detailed report of student's performance as a tutor and represents Quinn's feedback as a learner. An example of a feedback report is shown in Figure 4.2.

The information displayed in this report is the problem description, number of incorrect attempts Quinn made to reach the correct solution, the type of mistakes made divided by each incorrect attempt (with a prompt defining the mistake in detail), the total time taken to reach the correct solution, and the performance on the problem displayed in a visual manner with red filled circles with an 'X' for the number of incorrect attempts and green filled circle with a tick mark for the correct attempt. The type of mistake made is calculated by comparing student attempts with the set of identified misconceptions explained in Table 4.1. The research goal for this report is to analyze the effect of the learner report in enhancing Quinn's learning for future problems.

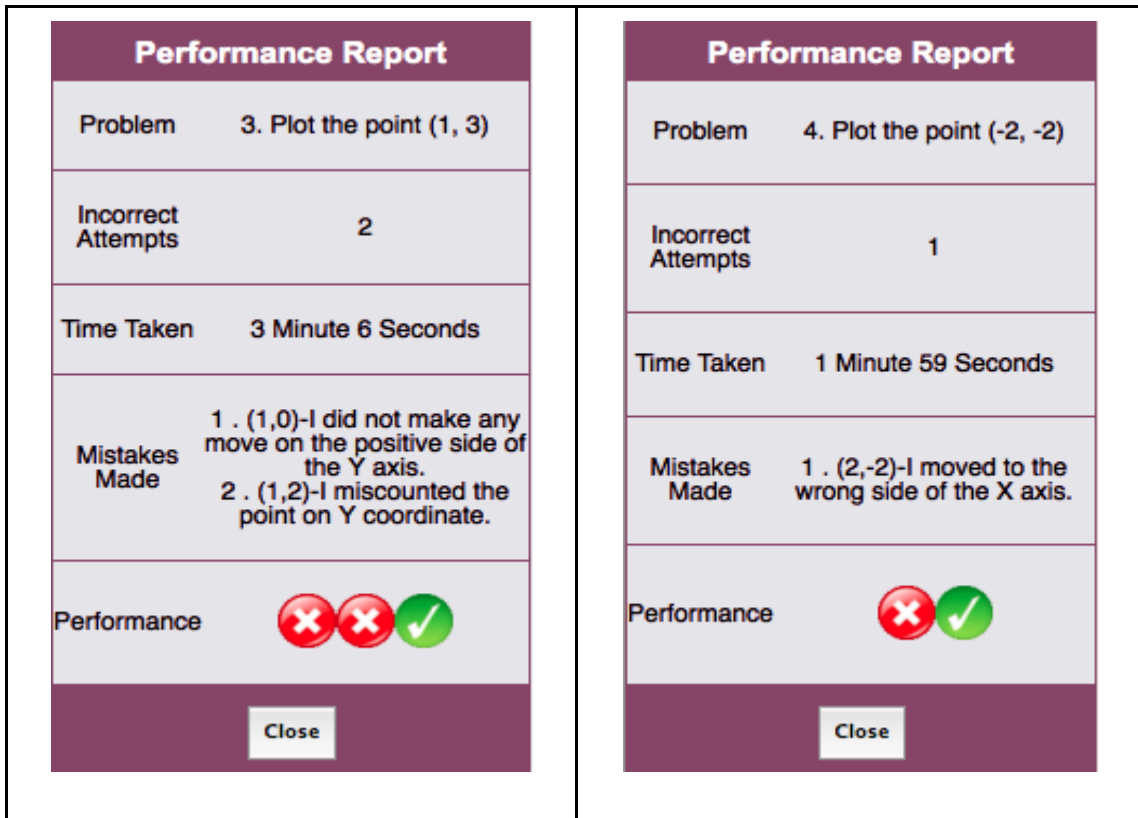


Figure 4.2: Feedback reports

### Graphical Report and Progress Report

The initial plan of this study included two additional reports: a graphical report and a progress report. The aim of the graphical report was to display student attempts in a visual format on the coordinate, system along with the best path to solve that problem. Figure 4.3 represents a prototype of the graphical report.

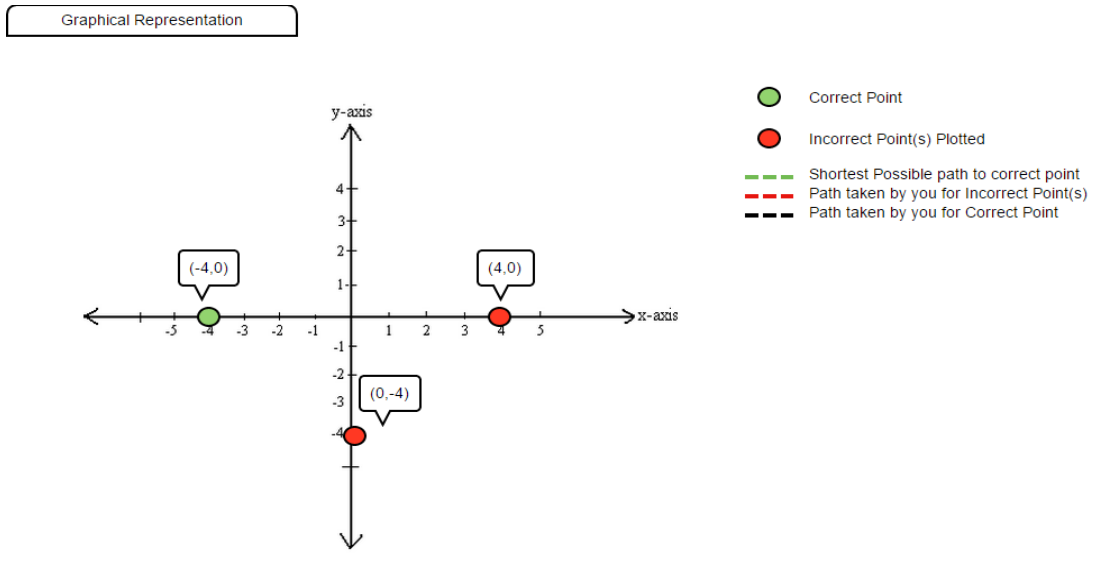


Figure 4.3: Prototype of graphical report

The aim of the progress report was to provide information on a student's overall progress based on the number of problems attempted and the type of axis involved. This report was designed in a format to visually appeal to middle school students. Figure 4.4 represents a prototype of the progress report.

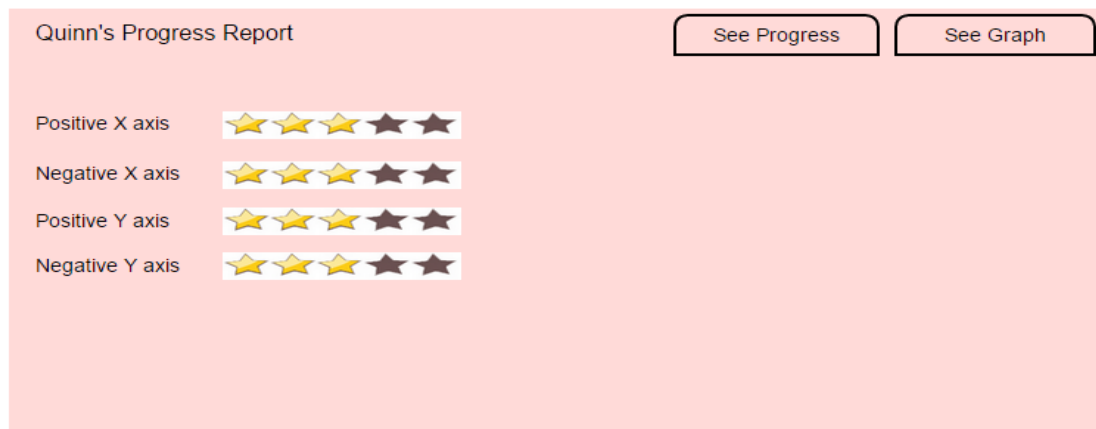


Figure 4.4: Prototype of progress report

The graphical and progress reports could not be implemented for this study for several reasons. The study was conducted with much older participants than the targeted age group; the reports

were more focused to the middle school environment and were not very relevant to the older participants. The information in both the reports was also included in the learner and feedback reports, and hence the data would have been repetitive.



## CHAPTER 5

### PILOT STUDY

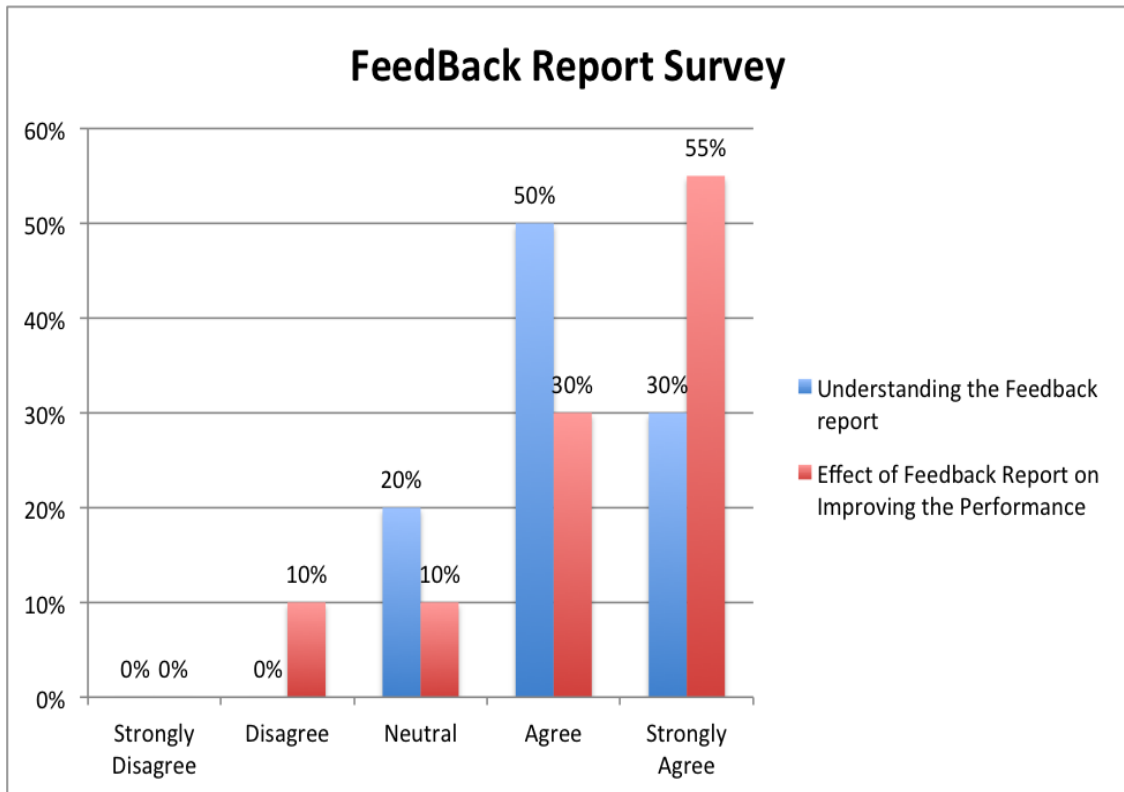
To implement the feedback report, I designed a pilot survey to analyze students' wishes about the content, effectiveness, and form of the two feedback reports. Students took the survey before the implementation phase. The goal of this survey was to discover student interest in the open learner model and feedback reports.

The pilot survey was done with 20 participants, of which 12 were male and 8 were female. The participants were in grades 5 and 6 from several schools in Tempe, Arizona.

#### ***5.1 Pilot Survey Results***

The pilot survey to analyze student interest in accessing the open learner model was conducted for feedback and learner reports. For the feedback report, a questionnaire was given to 20 students following a TAG study. The questionnaire had a short description about the idea of implementing the feedback report with an attached prototype, and a detail of the report. The questionnaire included two questions: 1) From the given prototype, how well do the students understand the feedback report? And 2) What will be the effect of the feedback report in improving student performance with Quinn? Responses were requested in the form of rating: 1 - Strongly Disagree to 5 - Strongly Agree.

Figure 5.1 shows the results of the feedback report survey. While most of the students agreed (50%) or strongly agreed (30%) that they understood the feedback report represented in the prototype, some (20%) were neutral in their input. The majority (55%) strongly agreed and (30%) agreed that the feedback report would be helpful in improving their performance; only a small percentage (10%) was neutral in their input.



*Figure 5.1: Results of pilot feedback report survey*

To measure student interest in the learner report, a similar questionnaire was administered with the same group in the above-mentioned study. The questionnaire had a short description about the idea of implementing the learner report and an attached prototype with a detail of the report. The questionnaire included two questions: 1) From the given prototype, how well do students understand the learner report? And 2) What will be the effect of the learner report in improving student performance with Quinn? Responses were requested in the form of rating: 1 - Strongly Disagree to 5 - Strongly Agree.

Figure 5.2 shows the results of the feedback report survey. For understanding the learner report a combined result of (35%) agreed and (30%) strongly agreed was in favor, whereas many (25%) were neutral in their response, and only a few (10%) disagreed on understanding the learner report. In response to the effect of the learner report in improving performance, the majority (65%)

agreed and (20%) strongly agreed.

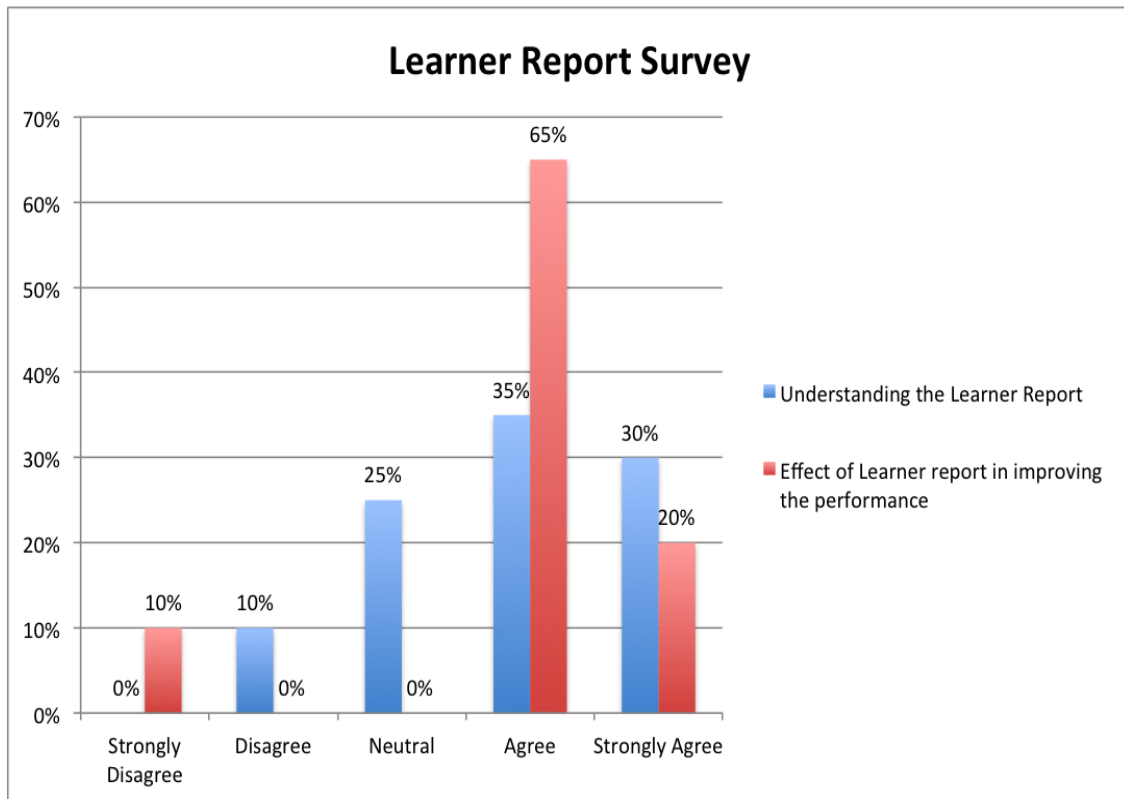


Figure 5.2: Results of pilot learner report survey

### Summary of Pre-implementation Survey Results

A positive response was experienced for the understanding and improvement in performance of both reports. A majority of students strongly agreed or agreed that the feedback report and the learner report integrated with Quinn would be effective in improving their performance. In terms of understanding, the feedback report was favorable, while that of the learner report got mixed responses.

### 5.2 Discussion of the Pilot Survey Results

The results of the pilot survey demonstrated that based on the prototype and the provided

overview, students supported the idea of implementing a feedback system in Quinn. The results were generally favorable toward understanding the feedback and learner reports. Students on average supported the claim that both the feedback and learner reports could be helpful in improving performance. The positive response for the feedback system survey suggested that many students took the idea of implementing feedback system in Quinn, positively.

## CHAPTER 6

### HYPOTHESIS AND METHODOLOGY

#### **6.1 Presentation of Hypothesis**

To analyze the effectiveness of the feedback system, several different factors were considered based on the learner report and the feedback report. First, the performance accuracy of students was measured in two different conditions; one, where the feedback and learner reports were displayed to the students, and two, where no feedback or learner report was displayed.

Comparing the number of correct and incorrect solutions students submitted during the study and pre/post-test assessment, the performance accuracy was calculated. Second, the performance efficiency of students was measured in two different conditions; one, where the feedback and learner reports were displayed to the students, and two, where no feedback and learner report was displayed. Third, the feedback on both the reports about various characteristics of the report was measured. This was calculated based on student input on a report questionnaire, which was given after the system usage.

The above factors were considered to prove the following hypothesis. I seek to determine whether the feedback and learner reports have an effect on the performance accuracy of students using TAG on a problem. Students should be able to retain more knowledge from the feedback report, which is represented after successful completion of a problem. Students should also maximize the use of content embodied in the learner report for understanding the misconceptions better for the problem they are attempting to learn. It is hypothesized that encountering the common misconceptions for a problem through the learner report will encourage students to be proactive in not repeating the represented misconceptions. The information given to the student through the feedback report will help the student to understand the domain better. Examining misconceptions will also help students better prepare for future problems. Both of these factors will lead to higher performance accuracy as compared to that of the students with

no feedback report.

To determine the effectiveness of learner and feedback reports for the above hypothesis, a report questionnaire was presented to students in each session. Student input on the questionnaire for the learner and feedback reports' content, effectiveness, advantage, and performance were used to analyze the reports' effect on student learning. The questionnaire was given to students in both the feedback report condition and non-feedback report condition. The results of this questionnaire allowed us to determine if the content of the reports helped students analyze their performance, improve their understanding, and increase their learning efficiency.

The hypothesis this work will investigate is:

H1: Students who are presented with the feedback and learner report will be able to understand the misconceptions for attempting the problem better. This will help them analyze their learning and performance, and hence they will solve the problem more accurately as compared to students who do not get any information in the form of a learner report for that problem.

## **6.2 Methodology**

This section explains the experimental design of the study used to collect data on the effects of the feedback system designed for the TAG system. Upon their arrival, participants were given an initial survey to gather information about background and comfort level with geometry. Then, each participant was given a pre-test to measure his or her prior knowledge. Before starting the session, each participant was given system training to familiarize him/her with how to guide Quinn to solve problems. After the training each participant was given approximately 25 minutes to teach Quinn to solve as many problems as they could. After the session, students were given a post-test to complete, along with two questionnaires. One questionnaire was to analyze their experience with Quinn. The second questionnaire was to determine their feedback on both the reports. The experimenter then conducts a short interview to gain information about student

perceptions of the feedback system.

### ***Participants***

The targeted participants for the study were 5<sup>th</sup> and 6th grade school students. Due to the recruitment constraints with schools and time constraints, the study was conducted with undergraduate students above the age of 18 from different non-science majors at Arizona State University, and with a preliminary knowledge of geometry. The participants were divided in two groups of 7 each. The first group, with 2 female and 5 male subjects, worked on the feedback system condition. The second group, with 4 female and 3 male subjects, worked on the non-feedback system condition.

### ***Measures***

An initial survey was given to students at the beginning of each session to record each subject's age, gender, and level of comfort with mathematics and geometry. After completion of the initial survey, students were given approximately 10 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 25 minute TAG experimental use session, students were given approximately 15 minutes to complete a post-test to assess their knowledge of the content utilized by TAG. They were also given two post-session questionnaires. 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 of student perceptions of the feedback system and their usability.

## CHAPTER 7

### RESULTS

#### 7.1 H1 Results

H1 stated “Students who are presented with the feedback and learner report are able to understand the misconceptions for a better attempt of the problem. This will help them analyze their learning and performance, and hence they can solve the problem with more accuracy as compared to students who do not get any information in the form of a feedback or a learner report for that problem.”

#### *Aggregate Student Performance Accuracy during TAG Usage*

To measure aggregate student performance accuracy of each group, the number of correct solutions submitted by all students in the *feedback system* and the *non-feedback system* group was compared to the total number of solutions submitted by all students in the same pool.

It was found that on average, of the 16 available problems students completed all the 16 problems with an average timing of 21.3 minutes using TAG. Of the 16, 15.64 problems were solved successfully. This shows that of all the submitted solutions, 96.87% were correct. The correct solutions submitted by the feedback system group that used TAG was 15.57, with an accuracy rate of 97.32%, while that of the non-feedback system group was 15.42, with an accuracy rate of 96.42%. A comparison of each condition’s average accuracy rate during TAG usage can be seen in Figure 7.1 below.



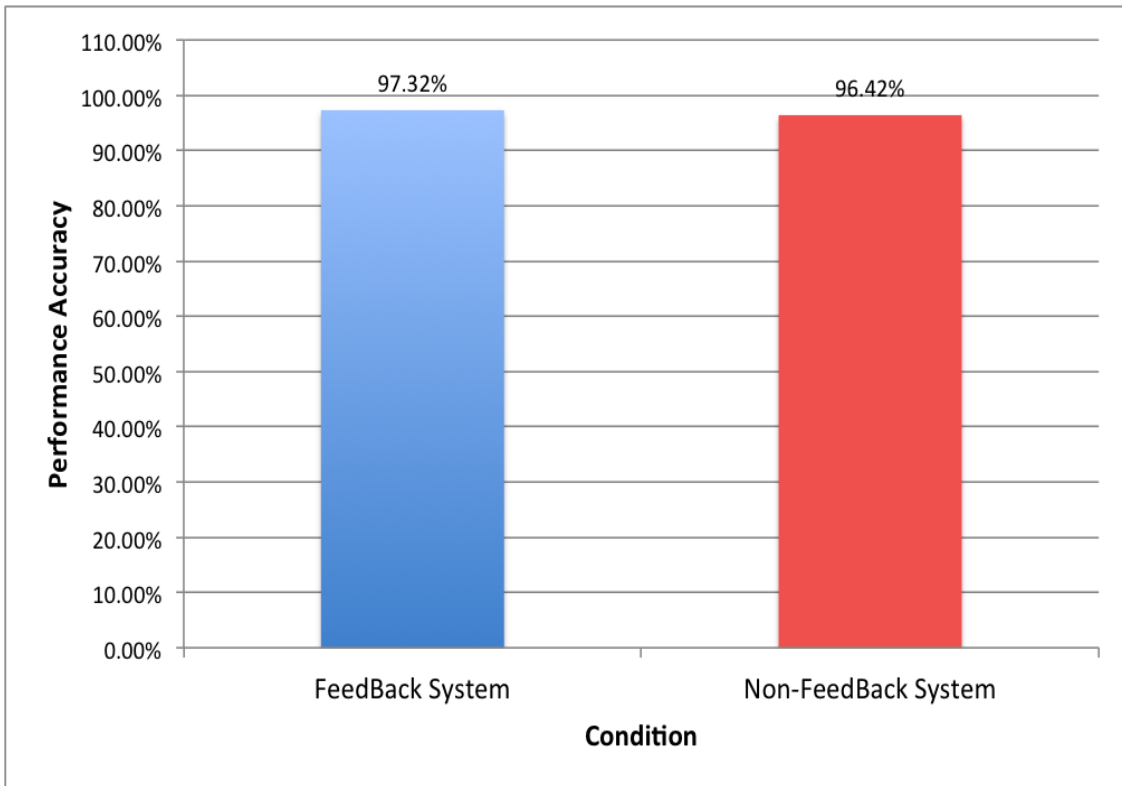


Figure 7.1: Results of performance accuracy

*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 (20) that a student could complete. All problems were scored with a binary grading system. Students could not receive partial credit for any problem.

It was observed that on an average, students scored 93.92% on the pre-test assessment and 95.7% on the post-test assessment. Students who encountered the feedback and the learner report from the *feedback system condition* during their use of TAG scored an average of 92.85% on the pre-test assessment and an average of 95.0% on the post-test assessment. Students who worked on the *non-feedback system condition* during their use of TAG scored an average of 95.0% on the pre-test assessment and an average of 96.42% on the post-test assessment.

In the feedback system condition, students showed an average improvement of 1.78% and in the non-feedback system students showed an average improvement of 1.42% between pre-test and post-test assessments.

Since the average improvement between the pre-test and post-test results in both the conditions was relatively small, to analyze the significant difference based on the mean value, the results were obtained through a one-way ANOVA test. The results are displayed in Table 7.1

	<b>N</b>	<b>Mean</b>	<b>Std. Deviation</b>	<b>F</b>	<b>Sig.</b>
Pre-Test 1.0	7	18.571	1.2724	0.491	0.497
2.0	7	19.000	1.0000		
Total	14	18.786	1.1217		
Post-Test 1.0	7	19.000	1.1547	0.300	0.594
2.0	7	19.286	0.7559		
Total	14	19.143	0.9493		

*Table 7.1: Results of ANOVA test of Pre- and Post-test*

As we can see from the results, the pre-test mean for group 1 (i.e., feedback system condition) is 18.571 and the standard deviation is 1.2724. For group 2 (i.e., non-feedback system condition), the mean is 19.000 and the standard deviation is 1. In the post-test results the mean for group 1 is 19.0 and the standard deviation is 1.154. For group 2, the mean is 19.286 and the standard deviation is 0.7559. The significant difference value for comparing the pre-test results is 0.497 and for the post-test results is 0.594. As analyzed from the statistics described above, there is no significant difference observed when comparing the pre-test results to the post-test results of both the groups.

For comparing the difference in the pre-test and post-test values of the two conditions distinctly, it

was calculated, as shown in Table 7.2, that the mean for the Feedback system condition is 0.429 and standard deviation is 1.3973, and the mean of non-feedback system condition is 0.286 and standard deviation is 0.4880. The significant difference value for these two conditions is 0.803.

	<b>N</b>	<b>Mean</b>	<b>Std. Deviation</b>	<b>Std. Error</b>	<b>F</b>	<b>Sig.</b>
1.0	7	0.429	1.3973	0.5281	0.065	0.803
2.0	7	0.286	0.4880	0.1844		
Total	14	0.357	1.0082	0.2695		

*Table 7.2: ANOVA results on the difference of pre- and post-test*

As analyzed from the result, there was no significant difference in the results of both the conditions. Hence, a strong performance improvement based on this comparison was not observed between the pre- and post-test of the two conditions.

#### *Aggregate Student Performance Efficiency during TAG Usage*

To measure the aggregate performance of students in each condition, the number of correct solutions submitted by all the students in both the conditions was compared to the total amount of time spent by all the students using TAG in both conditions. It was found that on average, of the 16 available problems, students in the feedback system and the non-feedback system condition completed all the problems. Students in the feedback system condition spent an average of 1.25 minutes per problem, with a standard deviation of 1.30 for an average rate of 15.57 correct attempts. On the other hand, students in the non-feedback system spent an average of 1.88 minutes per problem, with a standard deviation of 1.92 for an average rate of 15.42 correct attempts.

### *Summary of H1 Result*

The performance accuracy of the post-test as compared to the pre-test was on the higher side for both the conditions. The average performance accuracy improvement for the feedback system condition was also on the higher side when compared to the average performance accuracy improvement for the non-feedback system condition. The difference comparing the mean of pre-test for both groups to the post-test results of both groups was not significant. The significant difference comparing the difference of the pre- and post-test results of one group to another was not significant. Hence, based on these results no strong significance of the feedback system condition was observed over the non-feedback system condition. The differences between performance efficiency for students in the feedback system and non-feedback system condition during the TAG usage were minor.

### **7.2 Feedback System Survey Results**

Following the study and the post-test, a questionnaire was administered to the students based on the feedback and learner reports. Student input was measured on a scale of 1 - Strongly Disagree to 5 - Strongly Agree, for a given set of questionnaires for both the feedback system and the non-feedback system conditions. Students in the non-feedback system condition were given an overview of the feedback system condition after the completion of their study and their response was asked for; if given the option for the feedback report and the learner report, which condition would they prefer. Figure 7.2 describes the response of the 7 participants in the non-feedback system condition. A majority of the participants agreed (57.14%) and strongly agreed (28.57%), in preference of the feedback report. For the preference of the learner report, an equal response of 28.57% was received for agreed and strongly agreed, and a small ratio disagreed (28.57%) with the preference of learner report.

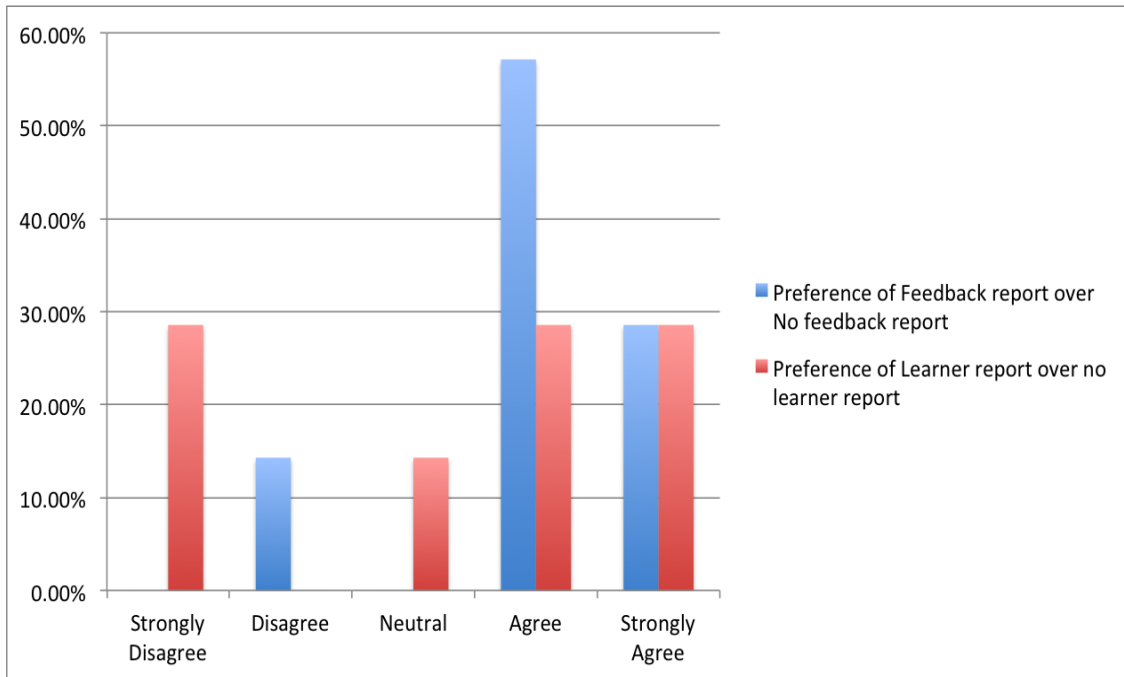


Figure 7.2: Results of post-implementation survey

For participants in both conditions, responses were taken on the content and understanding of the feedback and the learner report. Table 7.3 describes the average response of students for both the conditions on the effect of the feedback report.

Question	Condition	Average Response
How well did you understand the feedback report?	Feedback System	3.85
	Non-Feedback System	4.71
How well do you think the report helped improve your performance with Quinn?	Feedback System	3
	Non-Feedback System	3.42
How relevant were the content of the report for analyzing your performance With Quinn?	Feedback System	3.42
	Non-Feedback System	4

*Table 7.3: Average response of students on feedback report*

Table 7.4 describes the average response of students for both conditions on the effect of the learner report.

<b>Question</b>	<b>Condition</b>	<b>Average Response</b>
How well did you understand the learner report?	Feedback System	4.14
	Non-Feedback System	3.85
How well do you think the report helped improve your performance with Quinn?	Feedback System	2.85
	Non-Feedback System	3.14
How relevant were the content of the report for analyzing your performance With Quinn?	Feedback System	3.14
	Non-Feedback System	3.71

*Table 7.4: Average response of students on learner report*

*Summary of Feedback System Survey Result*

For both the feedback and the learner report, students showed more preference to work with the feedback system condition rather than non-feedback system. In terms of understanding the content, performance improvement, and relevance of the feedback and the learner report, students from the non-feedback system condition showed more positive results in favor of the report.

## CHAPTER 8

### DISCUSSION

This section will discuss the results of the presented hypothesis and the pre-implementation and post-implementation survey.

#### **8.1 Discussion of H1 Result**

This section will discuss the findings related to the accuracy of solutions submitted by the participants in the feedback system condition versus the accuracy of solutions submitted by the participants in the non-feedback system condition.

##### *Increased Performance Accuracy for Subjects in the Feedback System Condition during Pre/Post-Test Assessments*

Participants who encountered the feedback and learner reports showed minor improvement in terms of aggregate accuracy scores between pre-test and post-test assessments. Even though the difference in performance accuracy is insignificant, it does show a correlation between providing feedback about the understanding and performance of the student and short-term learning gains.

There are a few possible explanations for the negligible improvement of performance accuracy. First, prior research has demonstrated a connection between open learner models and learning gains. The reason that significant performance accuracy was not observed during this study may be because the study was conducted with participants with a significantly higher knowledge on the domain. It also might indicate that the benefits from using the feedback system in a teachable agent are more observable when testing for long-term retention of knowledge.

## **8.2 Discussion of Feedback System Survey Results**

The results of the post-implementation survey demonstrated that students from the non-feedback system condition preferred the feedback system condition for enhancing their performance with Quinn. Students on average showed a positive response on understanding the feedback and learner reports and relevance of the content. Students on average also supported the fact that both the feedback and learner reports will be helpful in improving their performance with Quinn. The post-implementation survey results demonstrate that students on average believed that the feedback system will benefit in improving their performance, and would be receptive of the feedback system condition in comparison with the non-feedback system condition. This supports our hypothesis that students in the feedback system condition will have more understanding of their performance and misconceptions, and hence will experience performance gain as compared to the students in the non-feedback system condition.

## **8.3 Conclusion**

The results of this study, which compares the effect using a feedback system with a teachable has on student performance, did not show a strong learning effect. The result of the post-implementation survey, analyzing the understanding and effect of the reports from both the conditions, also did not show a substantial difference. The slight percentage gain in performance accuracy result did not show a significant effect on the performance gain of the students in the feedback system condition over the students in the non-feedback condition. The minor difference was not adequate to conclude a positive result.

One limitation that may have contributed to the lack of difference in the results is the relatively older age of participants than the targeted age group. In addition, the minor performance gain does not guarantee a strong effect of the feedback system condition on the learning improvement



of students. The relatively positive responses in the pre-implementation survey, in support of understanding the reports and believing that the report will help to improve performance, supports the fact that students are receptive of working with a feedback system in teachable agents. The results of the post-implementation survey support that students are more desirable of working in the feedback system condition than the non-feedback system condition. It also indicates that students believed that the content of the feedback and the learner reports are relevant and will be helpful in improving their performance with Quinn. Though the studies' results did not show a progressive effect of the feedback system, the response of this survey indicates that students are receptive to working with the feedback system condition in Quinn.

Overall, considering the positive survey results and students' inclination to work with the reports (and keeping in mind that the limitation of executing the study with older participants) the results from this master's thesis indicate that the design of a teachable learning system should carefully consider incorporating an open learner model, allowing students access to their performance and learning information. Additional work should be done to determine how varying the types of reports and contents encountered in this type of feedback system can be used to increase learning efficiency with the teachable agent. 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. 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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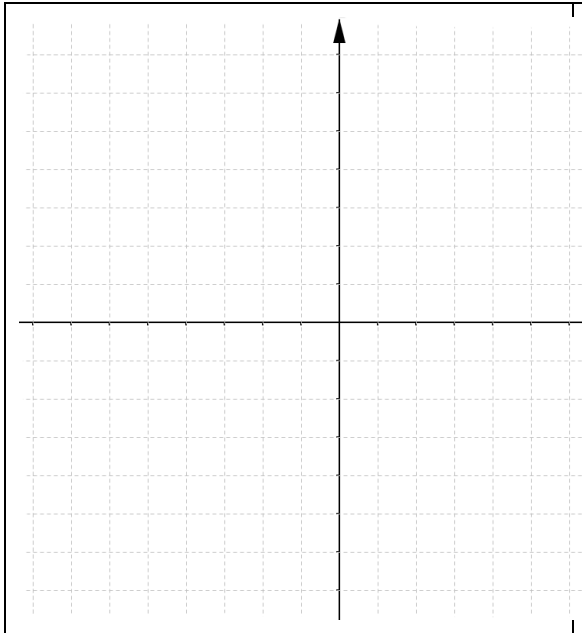
APPENDIX A

POST IMPLEMENTATION FEEDBACK AND LEARNER REPORT SURVEY





APPENDIX B  
PRE/POST-TEST ASSESSMENT



1. In the picture, **label**:

- x-axis
- y-axis
- Origin

2. With the point (3, 6), the **x-coordinate** is \_\_\_\_\_

3. With the point (5, 2), the **y-coordinate** is \_\_\_\_\_



