The Effects of Physical Form and Embodied Action in a Teachable Robot for Geometry Learning

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***Abstract*—A teachable agent is a learning companion that students teach about a domain they are trying to master. While most teachable agents have been virtual, there may be advantages to having students teach an agent with a physical form (i.e., a robot). The robot may better engage students in the learning activity, and if students take embodied action in order to instruct the robot, they may develop deeper knowledge. In this paper, we investigate these two hypotheses using the rTAG system, a teachable robot for geometry learning. In a study with 37 4th-6th grade participants, we compare rTAG to two other conditions, one where students use embodied action to teach a virtual agent, and one where students teach a virtual agent on a personal computer. We find that while there are no significant learning differences between conditions, students' perceptions of the agent are influenced by condition and prior knowledge.**

Keywords - robotic learning environment; teachable agent; personalized learning

I. Introduction

In 1988, Chan and Baskin outlined the idea of a computer as a learning companion, or a virtual agent that "learns" alongside a human student. Through the interactions between the virtual agent and human student, the virtual agent can improve the human student's learning [1]. One type of learning companion is a teachable agent, which simulates the collaborative activity of peer tutoring, in that the student teaches the agent about the target domain. Prior work has demonstrated that there are cognitive and social benefits to peer tutoring [2], and by extension, to having a student teach an agent [3]. However, it is not fully understood how to design a teachable agent to maximize student learning.

To date, the majority of teachable agent systems have been virtual. However, there may be several potential advantages to having students teach a robot rather than a virtual agent. First, the physical presence provided by a robotic agent strengthens users' perceptions of having a social partner more than a virtual agent, and thus may better socially engage students [4]. Second, students benefit from learning through embodied, physical interactions [5], which robotic platforms naturally support. In a robotic environment, the effects of a robot's social behaviors may be heightened; in an embodied environment, students may develop deep knowledge by linking concrete embodied representations to the underlying domain formalisms.

In our research, we use the robo-Tangible Activities for Geometry system (rTAG) to explore the impact of physical form on students' perceptions of a teachable agent, motivation, and learning. In rTAG, middle school students move within a projected coordinate system and interact with a robot named Quinn. They solve coordinate geometry problems [e.g., "Plot the point (3,1)"] by giving Quinn instructions to take actions such as "Move 3 units." Quinn responds to students with cognitive and social prompts.

In this paper, we survey related work, describe the rTAG system, and then present results from a study where we compare the rTAG system to two other conditions: a completely virtual version of TAG, run on a personal computer (vTAG), and a version of TAG where students interact in the embodied environment but with a virtual rather than robotic agent (eTAG). We hypothesize that rTAG will improve learning over the other two conditions because the robot will lead students to perceive the agent more positively and be more engaged. We close the paper with a discussion of the implications of our finding for future design of robotic learning environments.

II. Background

A. Teachable Agents

Teachable agents have emerged from the body of research on how students benefit from tutoring other students (e.g., [2]). The most investigated teachable agent system is Betty's Brain, designed to help students learn about causal modeling [6]. Students teach Betty, their agent, by using resources such as text and videos to draw causal networks. Students can ask Betty questions that she will answer based on the network, and at some point, Betty will take a quiz. Teaching a computer agent is highly beneficial for the student doing the teaching: it can lead to more learning than being taught by a computer agent [6], is nearly as effective as being taught by a human tutor [7], and can be more effective than classroom instruction [8]. When teaching an agent, students notice their own misconceptions and elaborate on their knowledge [6]. Moreover, students tend to be highly motivated to teach their agents, feel responsible for them, and so attend more to instructional material [3].

B. Robotic Learning Environments

Our research builds on the teachable agent paradigm by exploring the effects of a student teaching a robot. There are many platforms that provide students with the opportunity to *program* robots. One of the earliest systems was related to turtle geometry [9]. Students programmed a robotic logo turtle to turn and move, and a pen attached to it created geometric figures. When using programmable robot platforms like LEGO Mindstorms®, children are often asked to meet certain challenges, ranging from building a soccer playing robot to creating an interactive park [10]. These activities are successful at improving programming and robotics skills [11], but the evidence on whether mathematics and science outcomes are improved is less convincing, with existing quantitative evaluations of learning from robotics programs yielding mixed results [12].

While having students *teach* a robot is similar to having students program a robot, a robotic teachable agent should initiate interaction in ways that the programmable robot paradigm does not support. In fact, [13] characterizes the above approaches as using the robot as a passive tool, and suggest instead using robots as direct facilitators and coordinators for the learning activity, such that the robot responds in socially and cognitively appropriate ways. Use of a robot as an intelligent mediator is promising, with initial positive results arising out of instituting robotic learning companions in various settings [14, 15].

Along these lines, there have been a few examples of teachable robots for student learning. In [16], children aged 3-6 taught a Nao care-receiving robot how to act out particular English verbs. These children had improved vocabulary learning compared to a set of children who did not interact with the robot. In [17], students aged 6-8 taught a robot to write handwritten letters. This work is promising, but the benefits of teachable robots are not yet understood.

C. *Research Hypotheses*

Our work explores two hypotheses for why a teachable robot in an embodied environment might enhance learning. The first hypothesis is: **The social affordances of the robot will improve learning (H1a) and social perceptions of the robot (H1b).** Physical robots can increase social presence compared to virtual agents [18, 19], and strengthen users' perceptions of having a social partner [4]. These positive social perceptions of one's learning companion are considered an important factor for learning in computer-mediated environments [20, 21]. For example, [22] showed that students' positive interactions with a social assistive robot helped in developing geometric thinking and meta-cognitive skills. The social interactions fostered by the robot in rTAG may similarly improve student learning. Our second hypothesis is: **The embodied affordances of the activity will improve learning (H2a).** It has been proposed that humans give meaning to experience by going from embodied representations, using sensorimotor information, to symbolic representations [23]. There is much evidence that gesturing can facilitate learning [e.g., 24, 25], including complex gestural movements like sliding, stacking and/or rolling to mimic the shape of an object [26]. Thus, embodied action facilitated within our learning environment might improve student learning.

III. rTAG System

This paper uses a platform for tangible robotic learning called rTAG [27]. In rTAG, students are told they are giving instructions to a robot in order to teach it how to solve point-plotting problems. rTAG is currently comprised of the following three components (see Fig. 1, left). The *problem space* consists of a Cartesian plane projected onto a white foam mat. The *teachable agent*, Quinn, is an iPod Touch that displays facial expressions mounted on a LEGO Mindstorms® NXT 2.0 robot. Finally, the *mobile interface* consists of a second iPod Touch that students use to issue commands to the robot. Each one of these three components is a web app running from the same server.

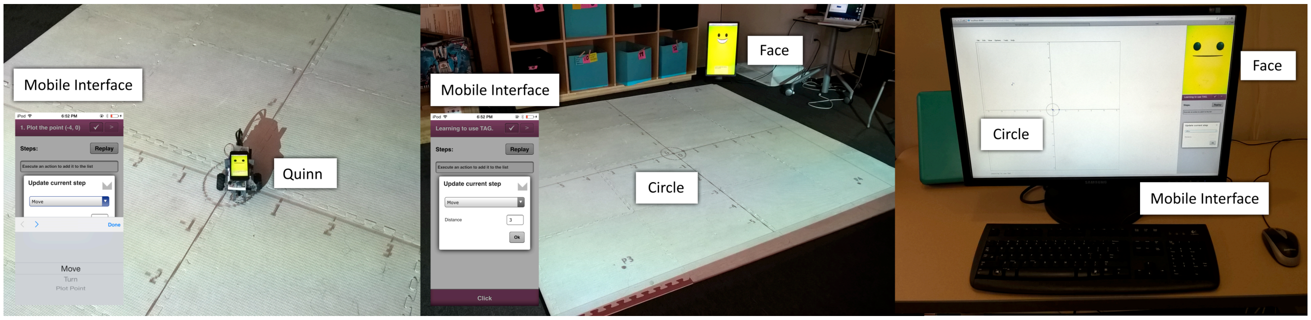
When using rTAG students are informed that they will be teaching Quinn to solve geometry problems. To issue commands to Quinn, students must first touch the iPod Touch that displays its face. When the face is touched, a list of commands available to the student appears on the mobile interface. This interface also lets the student see the current problem description and the steps taken thus far to solve it, check for correctness of the current solution, and, if the solution is correct, to move to the following problem. To illustrate, suppose a student is shown the following problem on the mobile interface: "Plot the point (2, 1)". At this point, Quinn will be at the origin with zero degrees of rotation. The student might tell Quinn to move 2 units, turn 90 degrees, move 1 unit, and then plot the point. To issue each command, the student has to touch Quinn's face.

When a command is issued, the robot moves to the correct place within the problem space. Its position is tracked by four Wii remotes attached to the ceiling, which capture the light from two sets of LEDs attached to the top of the robot. The communication between the system's components is done through Bluetooth in the case of computer-to-robot and Wii remotes-to-computer; and through a Wireless LAN network in the case of computer-to-iPods. Communication between web apps is done via web sockets.

To facilitate learning from rTAG, the robot provides cognitive support by generating prompts during and after problem solving, based on the student's current problem-solving state. The prompts include hints, self-explanations, and questions. Example prompts include: "I can't remember which way the y-axis goes! Do you? Can you walk along the y-axis for me?"; "In (4, 0), does the 4 tell me to move on the x-axis or on the y-axis?" Students are instructed to answer these prompts aloud.

rTAG also contains preliminary social support. Quinn's social behaviors are loosely based on attribution theory, and are generated in response to rTAG's feedback, representing the robot's reaction to whether it got the correct answer. Quinn's response includes an emotion displayed on its iPod and telling the student how it feels about the outcome (correct vs. incorrect solution) through a message spoken in a gender-neutral voice. In the message, Quinn attributes the outcome to factors along two dimensions: the cause of the outcome (effort or ability) and the agent responsible for it, namely itself, the student, or both. For example, Quinn might say, "Yay! I got that right because you are a good teacher."

Fig. 1. The three TAG conditions tested in the study. In rTAG (left), students interact with a robot, Quinn, using a mobile interface. In eTAG (center), students interact using the same mobile interface, and a projected circle responds to students' instructions. The agent's face is displayed on a screen to the side of the problem space. In vTAG (right), students interact with Quinn and the problem space through a computer.



Quinn avoids attributions that may provoke negative responses (e.g. attributing failure to the student's ability).

IV. Study Method

A. Conditions

To investigate our hypotheses regarding rTAG's effect on engagement and learning, we compared three conditions:

1. **rTAG.** This is the embodied teachable robot condition described in Section III. Students watched the robot take action in the physical space and interacted with the robot using both the iPod Touch mounted on the robot and the mobile interface (Fig. 1, left).
2. **eTAG.** This is the embodied teachable agent condition. Students still observed the problem being solved in a projected, physical space, but Quinn was represented by a projected circle rather than a physical robot. To make eTAG equivalent to rTAG in terms of the expressiveness of the agent, Quinn's face was displayed on a monitor beside the problem space (Fig. 1, center). Instead of touching Quinn's face to issue a command, students were instructed to touch the projected circle with the mobile interface iPod, and then tap on a "click" button available in the same device to trigger the list of commands. Thus, in both the rTAG and eTAG students had to move to the robot to issue commands, facilitating embodied action.
3. **vTAG.** This is the virtual teachable agent condition. Students interacted with a virtual version of TAG on a personal computer, consisting of both the coordinate space and Quinn's face (Fig. 1, right).

If H1a and H1b were true, one would expect rTAG to improve learning over eTAG and vTAG due to the social engagement engendered by rTAG. If H2a were true, one would expect rTAG and eTAG to improve learning over vTAG, due to the embodied action in rTAG and vTAG.

B. Participants & Procedure

Participants were 37 students recruited from the $4^{th,}$ 5^{th}, and 6^{th} grade (19 male, 18 female). We excluded one student who scored 100% on the pretest and one student who skipped several items on the self-report questionnaire, leaving 35 participants. Participants were randomly assigned to condition, leaving 10 students in rTAG, 12 in eTAG, and 13 in vTAG. The study took place both at our research lab and in a spare room at a school. Students received $20.

Students were introduced to the study, and then spent 5 minutes studying a Geometry cheat sheet that discussed the principles to be learned in the study. They were then given a 15-minute pretest, followed by a questionnaire on their attributional style (described below). They received 20 minutes of training on how to use the system. Next, students were given 45 minutes to solve problems with the system. If students made three incorrect attempts at a given problem, they were given a list of steps to correctly answer the problem, which they followed by themselves. Students solved a mean of 9.20 problems (SD = 5.89). After the 45 minutes, students took a 15-minute posttest, and then answered self-report questions on perceptions of their experience. In total, the study took two hours.

C. Measures

Pre- and posttests of domain knowledge were two isomorphic, counterbalanced forms, each consisting of 11 questions spanning factual knowledge (e.g. labeling the coordinate system), procedural knowledge (e.g. plotting points), transfer knowledge (e.g. units in the coordinate system) and embodied knowledge (e.g. moving direction when plotting points). Each item was assigned 0 or 1 point and then the total was summed to create the final score.

Perceptions of the robot were collected using [28]'s validated measurement tool for human-robot interaction, assessing perceived animacy (6 items), likability (5 items), intelligence (5 items), and trustworthiness (3 items). In this measure, students rate the agent on a series of 5-point scales (e.g., from foolish to sensible, unpleasant to pleasant, or artificial to lifelike). All items were averaged to create an overall measure of students' social perceptions.

V. Study Results and Discussion

A. Social Perceptions

First, we examined the effects of condition on student perceptions of the agent, testing H1b. We conducted four ANCOVAs, each with animacy, likability, intelligence, and trustworthiness as the dependent variable, condition as an independent variable, and pretest score as a covariate, as our initial analyses suggested that prior knowledge may be influencing student perceptions (see Table 1 for means). We found that condition had a marginally significant effect on likability ($F(2,29) = 3.26$, $p = 0.053$), and significant effects on intelligence ($F(2,29) = 3.59$, $p = 0.041$), and trustworthiness ($F(2,29) = 4.82$, $p = 0.016$). Effects of condition on animacy was not significant ($F(2,29) = 1.30$, $p = 0.29$). In addition, the interaction between condition and pretest score had a significant effect on trustworthiness ($F(2,29) = 4.64$, $p = 0.018$) and a marginal effect on likability ($F(2,29) = 3.18$, $p = 0.058$). We computed correlations for each condition between pretest and these two perception variables. For the vTAG condition, pretest was positively related to trustworthiness ($r(11) = 0.511$, $p = 0.074$) and likability ($r(11) = 0.457$, $p = 0.116$). For the eTAG condition, pretest did not seem particularly related to trustworthiness ($r(10) = 0.241$, p = 0.450) or likability ($r(10) = -0.016$, p = 0.960). For the rTAG condition, pretest score was negatively related to trustworthiness ($r(8) = -0.566$, p = 0.088) and likability ($r(8) = -0.489$, p = 0.151).

Interpreting these results, it seems as though low-prior knowledge students had more positive perceptions of Quinn in rTAG, while high-prior knowledge students had more positive perceptions in vTAG. It may be that high-prior knowledge students were likely to be more receptive to familiar technologies, while low prior knowledge students were more likely to be engaged by novel ones.

B. *Learning*

Next, we conducted a repeated-measures ANOVA to assess learning (H1a and H2a). Test score was the dependent variable, test time was used as a within-subjects variable, and condition was used as a between-subjects variable (see Table 1). Students improved significantly from pre to posttest ($F(1,32) = 40.76$, $p < 0.001$), but there was no significant differences between conditions in terms of learning ($F(2,32) = 0.423$, $p = 0.658$).

We had posited a relationship between students' social perceptions and their learning. As an exploratory analysis, we ran a series of partial correlations within each condition where we controlled for pretest score and explored the effects of students' social perceptions on their posttest scores. While no correlations were significant, within the rTAG condition, we found negative relationships between posttest score and perceived likability ($r(7)= -0.528$), and posttest score and trustworthiness ($r(7) = -0.227$). This pattern was stronger in the eTAG condition, with posttest score negatively related to likability ($r(9) = -0.650$), animacy ($r(9) = -0.329$), intelligence ($r(9) = -0.477$), and trustworthiness ($r(9) = -0.441$). We did not find this pattern in the vTAG condition, and, in fact, posttest score appeared to be positively related to perceived intelligence ($r(10) = 0.331$) and likability ($r(10) = 0.202$).

Thus, there was little evidence that social perceptions positively related to learning within the two embodied conditions. In fact, the added motivational elements may have increased cognitive load, adding "seductive details" that distracted the learners [29]. The more students attended to novel features of the technology, the less they may have attended to the problem-solving content.

VI. CONCLUSIONS

In this paper, we examined the effects of a teachable robot on student perceptions and learning, compared to virtual and embodied versions of the system. While students learned from using the system, there were no significant differences between conditions on learning. There was some evidence that perceptions influenced learning, although in unexpected ways. Students with low prior knowledge appeared to respond more positively to rTAG, suggesting that the novelty of the system and the robot may have appealed to them. However, positive perceptions of rTAG were related to smaller learning gains. Students with more positive perceptions of rTAG may have been distracted by its novel elements [29].

Our analysis was limited by our small sample size, which reduces the generalizability of the findings. In addition, the short duration of the study makes it difficult to interpret the results. Two hours may not give students enough time both to learn how to use the system and to reflect on the problem-solving content. Short-term interactions with technology can produce a novelty effect, where students' initial engagement decreases after the first few interactions [30].

Thus, there is a need for additional research examining

TABLE I. MEANS AND STANDARD DEVIATIONS (IN PARENTHESIS) FOR SOCIAL PERCEPTION AND LEARNING VARIABLES. PRETEST AND POSTTEST SCORES ARE REPORTED AS PERCENTAGES. SOCIAL PERCEPTION SCORES ARE OUT OF 5.

	Animacy	Likability	Intelligence	Trustworthiness	Pretest	Posttest
vTAG	3.92 (0.94)	4.46 (0.96)	4.19 (0.73)	4.33 (0.73)	38.8 (24.1)	57.0 (25.6)
eTAG	3.87 (0.76)	4.62 (0.36)	4.40 (0.55)	4.64 (0.39)	45.8 (32.0)	58.7 (30.1)
rTAG	4.53 (0.67)	4.66 (0.49)	4.56 (0.46)	4.53 (0.67)	40.3 (23.0)	55.9 (17.2)

whether low prior knowledge students are socially engaged by the robot over long periods of time, and if so, how best to support them in learning. Iteration on the cognitive and social support within the system may preserve students' motivation while better directing their attention to salient problem-solving features. For example, we could investigate how different types of social statements can lead students to reflect on problem-solving steps. In addition, use of rTAG in classroom contexts may yield secondary benefits, facilitating collaboration and technological literacy in addition to problem-solving [27]. Teachable robots hold theoretical promise, but require continued research into relevant design principles and their potential effects.

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