

# Impact of Prior Knowledge and Teaching Strategies on Learning by Teaching

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**Abstract.** We investigate cognitive factors that are predictive of learning gains when students learn to solve equations by teaching a synthetic peer, called SimStudent. Previous empirical studies showed that prior knowledge is strongly predictive of post-test scores. However, in a recent study in the Philippines that replicated our previous study in the USA, there were students with low prior-knowledge who tutored their SimStudent better than other equally low prior students. In this paper, we analyze both process data (tutoring interactions) and outcome data (test scores) to understand what makes learning by teaching more effective. The results imply a presence of individual behavioral differences beyond the difference in the prior knowledge that might have affected SimStudent's learning, which in turn had non-trivial influence on tutor learning.

**Keywords.** Learning by teaching, teachable agent, SimStudent, Algebra equations, prior knowledge

## 1. Introduction

Since the late 1990s, researchers have investigated intelligent tutoring systems with intelligent pedagogical agents (often called *teachable agents*) to study a promising type of learning where students learn by teaching [1-3]. These technologies allow researchers to conduct tightly controlled experiments and to collect detailed *process data* representing interactions between students and teachable agents that together provide empirical evidence for the benefit of learning by teaching [4].

Matsuda *et al.* (in print), for example, showed that students' learning significantly correlated with the learning of teachable agents. Biswas *et al.* [5]

studied whether students could learn to self-regulate their teaching activities and how the ability of self-regulation affects the tutor learning. It is therefore of intellectual interest to uncover how the tutoring interaction affects students' learning by teaching.

In the current study, we use SimStudent, which is a teachable agent that helps students learn problem-solving skills by teaching [6]. It has been tested and redesigned several times, resulting in insights regarding the effects of learning by teaching and related cognitive theories to explain when and how students learn by teaching. Previous studies showed that pre-test score were highly predictive of post-test scores when students learn equation solving by teaching SimStudent [7]. In general, when students do not have sufficient prior knowledge on the subject to teach, they are not able to teach correctly and appropriately hence the benefit of learning by teaching would be arguably decreased.

Nonetheless, there are some students with low prior knowledge who learned more than others by teaching SimStudent. Among equally low-prior students, those who showed better performance on the post-test actually tutored their SimStudent better as well. The difference in the learning gain among students with comparable prior-knowledge indicates a presence of effective interaction for learning by teaching that might bootstrap tutor learning even with insufficient prior knowledge.

The goal of this paper is to investigate cognitive factors that affect tutor learning. The central research question is why some students (even with low prior knowledge) learned more than other students with comparable prior knowledge. To address this research question, the current paper analyzes data from two classroom (in-vivo) studies conducted in the USA and the Philippines. The Philippines study was a replication of the USA study reported earlier [8].

In the rest of the paper, we first introduce a learning environment in which students learn to solve linear equations by teaching SimStudent. We will then introduce two classroom studies conducted in the USA and the Philippines followed by the results and discussions.

## **2. Online Learning Environment with SimStudent**

This section provides a brief overview of SimStudent and the online learning environment, Artificial Peer Learning environment using SimStudent (APLUS), in which students learn to solve algebra equations by interactively teach SimStudent. Technical details about SimStudent and APLUS can be found elsewhere [7]

### **2.1. SimStudent**

SimStudent is a synthetic pedagogical agent that acts as a peer learner. It learns procedural skills from examples. That is, a student gives SimStudent

a problem to solve. SimStudent then attempts to solve the problem one step at a time, occasionally asking the student about the correctness of each step. If SimStudent cannot perform a step correctly, it asks the student for a hint. To respond to this request, the student has to demonstrate the step.

Students may not be able to provide the correct feedback and hints. As SimStudent is unable to distinguish correct from incorrect feedback, it continues to try to generalize examples and generate production rules that represent the skills learned. SimStudent is also capable of making incorrect inductions that would allow SimStudent to learn incorrect productions *even when students teach SimStudent correctly*. SimStudent's ability to model students' incorrect learning is one of the unique characteristics of SimStudent as a teachable agent.

## 2.2. APLUS: Artificial Peer Learning Environment using SimStudent

Figure 1 shows an example screen shot of APLUS. In APLUS, students act as a tutor to teach SimStudent how to solve equations. SimStudent is named Stacy and visualized at the lower left corner of APLUS. The tutoring interface allows the student and Stacy to solve problems collaboratively. In the figure, a student poses the problem  $3x+6=15$  for Stacy to solve. Stacy enters "divide 3" and asks the student whether this is correct. The student responds by clicking on the [Yes/No] button. If the student gets stuck, she can consult the examples tabbed at the top of the screen.

The student has the option of gauging how much Stacy has learned with the use of a quiz. The student chooses when and how often to administer

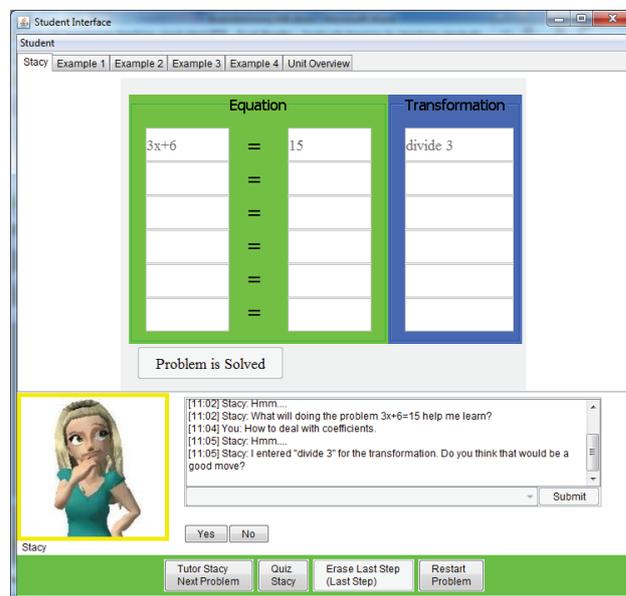


Fig 1. A screen shot of APLUS. SimStudent is visualized with an avatar image and names Stacy.

the quiz by clicking a button at the bottom of the interface. The quiz interface looks like the tutoring interface, however, when Stacy takes the quiz, she does so independently, without any feedback or intervention from the student. At the end of the quiz, the student is presented with a quiz result.

The quiz is divided into 4 sections, each with two equation problems. The quiz items were created from the mix of one-step, two-step, and target equations (i.e., the equations with variables on both sides).

Stacy cannot progress to a section until she passes the previous section. The students were asked to tutor Stacy to be able to solve equations with variables on both sides. In the classroom studies, the students were informed that their goal was to help Stacy pass all four (4) sections of the quiz.

### **3. Methods**

#### **3.1. Participants**

The USA study took place in one high school in Pittsburgh, PA, under the supervision of the Pittsburgh Science of Learning Center [8]. There were eight Algebra I classes with an average of 20 students per class. A total of 160 students with ages ranging from 14 to 15 participated in the study.

The Philippines study took place in one high school in Manila, Philippines, under the supervision of the co-authors from the University of the East and the Ateneo de Manila University. We enlisted participation from five first year high school sections with an average of 40 students per class. There were 201 study participants in all with ages ranging from 11 to 15. The average age of the participants was 12.5 years.

#### **3.2. Structure of the study**

In both the USA and the Philippine studies, each participant was randomly assigned to one of two versions of SimStudent: an experimental condition in which Stacy prompted the participants to self-explain their tutoring decisions and a control condition with no self-explanation prompts. The study was designed this way to investigate a particular research question on the effect of self-explanation for tutor learning [8], which is beyond the scope of the current paper. For three consecutive days, participants used their assigned version of SimStudent for one classroom period per day (42 minutes for the USA and 60 minutes for the Philippines study).

#### **3.3. Measures**

Students took pre- and post-test before and after the intervention. The students also took a delayed-test two weeks after the post-test was administered. Three versions of isomorphic tests were randomly used for pre-, post-, and delayed-tests to counterbalance the test differences. Students had the entire class period to finish the tests.

The tests are divided into five parts. Of these five parts, three parts are to test procedural knowledge on how to solve equations (the Procedural Skill Test, or PST), whereas other two parts are to test conceptual knowledge about algebra equations (the Conceptual Knowledge Test, or CKT). 102 out of 160 USA participants took all three tests, whereas in the Philippines 146 out of 201 participants took all three tests. In the following analyses, unless otherwise indicated, only those students who took all three tests are included.

The system automatically logged all of the participants' activities including problems tutored, feedback provided, steps performed, examples reviewed, hints requested, and quiz attempts. In the following analysis, we use these factors as process data.

## 4. Results

### 4.1. Overall Test Scores

Table 1 shows mean test scores plus or minus SD for the pre, post, and delayed Procedural Skill Tests from two studies. To see how students' test scores varied before and after teaching SimStudent, we conducted a two-way repeated-measures ANOVA with condition as a between-subjects variable and test-time (pre, post, and delayed) as a within-subjects variable. For the USA study, the repeated measure analysis revealed a weak trend for the main effect for test-time. A post-hoc analysis detected a difference from pre-test to post-test [8]. In the Philippines study, the test-time was also the main effect, and the post-hoc analysis detected that delayed-test was significantly higher than pre-test;  $t(247.1) = 2.457, p < 0.05$ . This difference, however, was likely due to the classroom instruction that students were taking during the two-week interval between the intervention and the delayed test.

Both in the USA and the Philippine studies, condition was not the main effect—the presence of self-explanation did not affect tutor learning with the version of APLUS and SimStudent used in two studies.

**Table 1:** Mean test scores  $\pm$  SD for pre, post, delayed procedural skill test for each study.

	Pre-test	Post-test	Delayed-test
Philippines (PH)	0.21 $\pm$ 0.01	0.22 $\pm$ 0.02	0.25 $\pm$ 0.03
USA (US)	0.68 $\pm$ 0.04	0.71 $\pm$ 0.05	0.69 $\pm$ 0.06

### 4.2. Impact of prior knowledge

As shown in Table 1, there was a notable difference in the pre-test scores suggesting that USA students had higher level prior knowledge than Philippine students;  $t(142.4) = -22.25, p < 0.001$ .

To see how prior knowledge affected learning and if the impact of prior knowledge differ between two studies, we ran a regression analysis with post-test score as a dependent variable and study (US vs. PH) as a fixed factor using pre-test score as a covariate. The results showed that pre-test is a strong predictor of post-test;  $t(244) = 2.80, p < 0.01$ . There was also a strong interaction between pre-test and study; the regression coefficient (slope) differed significantly between two studies;  $b_{PH} = 0.32$  vs.  $b_{US} = 0.76$ ;  $F(1,244) = 11.24, p < 0.001$ —suggesting that, in general, USA students gained (from pre- to post-test) more than Philippine students. Figure 2 shows the scatter plot for pre-test (x-axis) and post-test (y-axis) scores. USA students (red triangles) had steeper regression line than Philippine students.

### 4.3. Quiz Results

In the USA study, 36 out of 102(35%) students made their SimStudents pass all four quiz sections. In the Philippines study, no students passed all four sections. At the best, only 7 out of 146 (5%) of Philippine students had their SimStudents pass quiz section 2.

In the Philippines study, there were 73 students who solved quiz item #1 correctly. Of those 73 students, 68 students solved quiz item #2 correctly (hence by definition passing quiz section 1). Of those 68, only 11 students passed quiz section 2 (i.e., solving the first four quiz items correctly).

One possible explanation for the Philippine students' poor performance on the quiz is that Philippine students have insufficient prior knowledge, as indicated by the low pre-test scores and the weak regression slope. A number of factors may account for the difference prior knowledge, including curricular and age differences.

Still, some Philippine students managed to solve the first four quiz items (i.e., passing the quiz section 2), while others did not. Why might this be so? The next section addresses this issue.

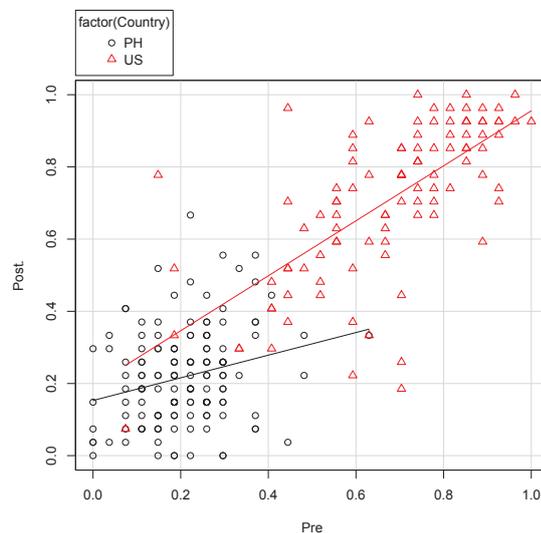


Fig. 2: Scatter plot of pre-test (x-axis) and post-test (y-axis) scores. US students had larger regression slope (0.76) than the PH students (0.32).

#### 4.4. What makes learning by teaching more effective?

To understand why some SimStudents performed better on the quiz than others, we have analyzed the process data. In this analysis, we grouped students depending on the quiz sections their SimStudents passed. We call students whose SimStudents passed and failed quiz section  $x$  the “passing  $Sx$ ” and “failing  $Sx$ ” students, respectively. By definition, there were no passing S3 students in the Philippines study.

Our focus in this particular analysis is to understand how some students managed to pass quiz sections in the Philippines study. Therefore, we only included Philippine students for this analysis unless otherwise noted.

##### 4.4.1. Accuracy of tutoring

One cognitive factor that had a significant contribution to tutor learning in the past studies is the accuracy of tutoring—i.e., the accuracy of recognizing correct and incorrect steps made by SimStudent as well as the accuracy the steps demonstrated as hint.

We thus compared the mean accuracy of passing/failing S1 and S2 students. The result suggested that the accuracy of tutoring is a key for success on the quiz in the Philippines study as well. For S1:  $M_{Passing} = .70$  (SD = .14) vs.  $M_{Failing} = .52$  (SD = 0.16);  $t(119.3) = -6.89$ ,  $p < 0.001$ . For S2:  $M_{Passing} = .75$  (SD = 0.09) vs.  $M_{Failing} = .59$  (SD = 0.18);  $t(8.7) = -4.39$ ,  $p < 0.01$ .

Students’ prior knowledge should have affected tutoring accuracy. There was actually a strong correlation between the prior knowledge (measured as the pre-test score on the Procedural Skill Test) and the accuracy of tutoring. There was also a study difference—USA students tutored more accurately than Philippine students. The centered polynomial regression with the centered pre-test score (i.e., the difference from the mean) as the covariate (C.Pre) and the study (US vs. PH) as a fixed factor predicting the accuracy of tutoring (AT) revealed the following regression coefficients:  $AT = 0.62 + 0.16 * C.Pre + 0.18 [if US]$ ;  $r^2 = 0.42$ ,  $F(2, 235) = 88.31$ ,  $p < 0.001$ ; meaning that *Philippine students at the average procedural skill pre-test tutored with a 62% accuracy rate. USA students tutored 18% more accurately than Philippine students in general.* There was no study difference for the regression slope—suggesting that the prior knowledge affected the accuracy of tutoring equally in two studies.

A further analysis that compared passing and failing S1 students revealed that the prior knowledge was not the dominant factor that affected the accuracy of tutoring. In the Philippines study, the average pre-test score of the Procedural Skill Test for passing S1 students ( $M = .21$ ,  $SD = 0.10$ ) was not higher than failing S1 students ( $M = .20$ ,  $SD = 0.09$ ). However, the average accuracy of tutoring was higher for passing S1 students ( $M = .70$ ,  $SD = .14$ ) than failing S1 students ( $M = .52$ ,  $SD = 0.17$ ).

As for the students’ learning, there was a weak trend on the average normalized gain from pre- to post- favorable to passing S1 students ( $M = .05$ ,  $SD = 0.22$ ) than failing S1 students ( $M = .01$ ,  $SD = 0.18$ );  $t(92.3) = -0.46$ ,  $p = 0.65$ .

This indicates that *the passing S1 students in the Philippines study learned more by teaching than the failing S1 students although there was no significant difference of the prior knowledge among them*. There might have been difference in the way passing and failing S1 students tutored SimStudent. The next section shows the results on analyzing process data.

#### 4.4.2. Tutoring strategies

Since quiz items were fixed, using quiz items for tutoring could be a good strategy to help SimStudent pass the quiz. Actually, in the USA study, passing S4 students showed a higher percentage of using quiz problems for tutoring ( $M_{US} = .95$ ,  $SD = .11$ ) than failing S4 students ( $M_{PH} = .59$ ,  $SD = .42$ );  $t(28) = -4.08$ ,  $p < 0.001$ .

Thus, we first investigated whether passing S1 and S2 students in the Philippines study used more quiz items for tutoring than failing S2 students. We found that only 47% (1826 out of 3898) problems tutored in the Philippines study were the quiz items. Philippine students did not copy quiz items for tutoring as often as the successful (i.e., passing S4) USA students.

If time on task were a crucial factor for learning by teaching, then students who tutored on more problems should have learned more than those who tutored on fewer problems. To test this hypothesis, we first analyzed if passing S1 students simply tutored more problems than failing S1 students. The average number of problems tutored was  $28.9 \pm 14.6$  for passing S1 students and  $20.9 \pm 12.2$  for failing S1 students. The difference was not statistically significant. There was no notable difference in the number of problems tutored between passing and failing S1 students.

#### 4.4.3. Resource usage

Did passing S1 students self-learn the materials by using resources more than failing S1 students? When counting the number of times students referred to worked-out examples, there was actually a notable difference. The passing S1 students referred to worked-out examples more than failing S1 students;  $M_{Passing\ S1} (N=52) = 164 \pm 116$  vs.  $M_{Failing\ S1} (N=79) = 106 \pm 94$ ;  $t(93.19) = -3.00$ ,  $p < 0.01$ .

Furthermore, passing S1 students copied more example problems for tutoring than failing S1 students;  $M_{Passing\ S1} = 2.2$  vs.  $M_{Failing\ S1} = 1.4$ ;  $t(111.16) = -3.62$ ,  $p < 0.001$ . Even when students did not actually understand how to solve equations, they could simply copy worked-out examples line by line to tutor SimStudent, which should have certainly affected SimStudent's ability to pass the quiz.

There was also a significant correlation between the number of example problems tutored and number of times example tab were clicked;  $r^2=0.36$ ,  $t(133)=8.67$ ,  $p < 0.001$ —suggesting that *Philippine students were actually switching between tutoring interface and example tabs frequently when they were copying example problems and their solutions for tutoring*.

#### 4.4.4. Predictor of learning

Since there were several factors that contributed SimStudent's and students' learning found in the data, we conducted a regression analysis to see how certain factors contributed to the post-test score on the procedural skill test. The following variables were entered in the regression model: pre-test score on the Procedural Skill Test, total number of problems tutored, total number of quiz items tutored, total number of examples viewed, total number of example problems tutored, accuracy of tutoring, and study.

The result showed that pre-test score, accuracy of tutoring (AT), and study were significant predictors of post-test score (PTS) on the Procedural Skill Test. When pre-test score was centered (C.Pre), the following regression coefficients were revealed:  $PST = 0.21 + 0.61 * C.Pre + 0.23 * AT + 0.14 [if US]; r^2 = 0.77, F(3, 234) = 267.7, p < 0.001$ . Since pre-test and accuracy of tutoring are highly correlated, dropping accuracy of tutoring from the model also showed an equally good fit:  $PST = 0.34 + 0.63 * C.Pre + 0.34 [if US]; r^2 = 0.76, F(2, 245) = 399.3, p < 0.001$ .

## 5. Discussions and Concluding Remarks

We found that the prior knowledge had a strong influence on tutor learning—if students do not have sufficient prior knowledge for tutoring, they would not benefit from tutoring as much as students who have appropriate prior knowledge. The regression model mentioned in the results section shows that prior knowledge is the dominating predictor of post-test score for the Procedural Skill Test.

Nonetheless, in the Philippines study, students who managed to have their SimStudent pass the first quiz section (i.e., the first two quiz problems) outperformed those who failed to do so on the post-test of the Procedural Skill Test (albeit the small effect size) even when there was no pre-test difference between passing and failing students. Students who tutored SimStudent better learned more. The same correlation between SimStudent's and students' learning was observed in previous studies [7].

These results indicate that some students had actually learned how to tutor better SimStudent via the actual tutoring interaction. We found that, in the Philippines study, students who managed their SimStudent to pass the first two sections of the quiz copied worked-out examples more often than those who failed to pass the quiz. Furthermore, those passing students reviewed the worked-out examples more often than failing students. Further investigation would be necessary to understand how to better assist students with low prior knowledge to learn by teaching.

Learning by teaching is a promising type of learning especially when combined with an advanced agent technologies. Yet, there are many to understand when and how students learn by teaching and how to best facilitate their learning with various individual differences.

## 6. Acknowledgements

The authors thank the Ateneo Laboratory for the Learning Sciences, Marc Lester Armenta, Regina Ira Antonette M. Geli, Victoria Keiser, Gabriel Jose G. Vitug, and Evelyn Yarzebinski. We thank the Department of Science and Technology Philippine Council for Industry, Energy, and Emerging Technology Research and Development (PCIEERD) for the grant entitled, "Development of Affect-Sensitive Interfaces" and the Engineering Research and Development for Technology (ERDT) program for the grant entitled, "Development of an Educational Data Mining Workbench."

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