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Competency-oriented Learning by Teaching is as effective as Mastery Learning provided by Cognitive Tutor

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The effect of Learning by Teaching and learning by being tutored was compared for learning linear equations. Three versions of an online learning environment were created: (1) APLUS for Learning by Teaching, (2) AplusTutor that is a cognitive tutor without problem selection adaptation, and (3) CogTutor+ that is equivalent to the traditional cognitive tutor. A randomized controlled study was conducted in two public schools with 184 7th and 8th grade students. The results showed (i) students' in the AplusTutor condition finished the quiz quicker than students in the APLUS condition, and (ii) there was a notable difference between Learning by Teaching and learning by being tutored in the "effort" students made.

1. Introduction

Learning by Teaching is a promising style of learning that has been empirically studied in various educational settings with remarkable positive effects in many subject domains [1, 2]. In recent years, researchers use the teachable agent technology to build an online learning environment that allows students to learn by teaching a synthetic peer, often called a teachable agent [3]. In the previous studies, the effect was often measured relative to traditional classroom instruction [4] or with different scaffolding strategies [6]. Learning by Teaching has rarely been compared with other types of instructional strategy. To advance the theory of Learning by Teaching, it is necessary to understand the similarities and differences between Learning by Teaching and other types of instructional strategy.

The goal of this study is to compare the effect of Learning by Teaching with learning by being tutored (aka cognitive tutoring [7]). We used an existing online learning environment for Learning by Teaching—APLUS (Artificial Peer Learning environment Using SimStudent)—where students can interactively teach a teachable agent called SimStudent [5]. As a comparison, we developed two versions of cognitive tutors using the APLUS interface—AplusTutor and CogTutor+. A classroom study was conducted to measure the effect of these three types of learning technologies.

2. Evaluation Study

Students using APLUS (Fig. 1) act as a tutor. The goal for students is to have their SimStudent pass the quiz. The quiz has four sections based on difficulty. One Step Equation (1 problem), Two Step Equations (2 problems), Equations with Variables on Both Sides (4 problems) and Final Challenge (8 problems, which is all equations with variables on both sides). SimStudent then applies what it has learned thus far to solve the quiz problems. There are learning resources available for students to review,:: (1) Problem Bank (a list of suggested equation problems to teach SimStudent), (2), Introduction Video (shows students how to use APLUS), (3) Unit Overview (a brief overview of how to solve algebra equations) and (4) Examples (worked-out examples for the target quiz level equations).

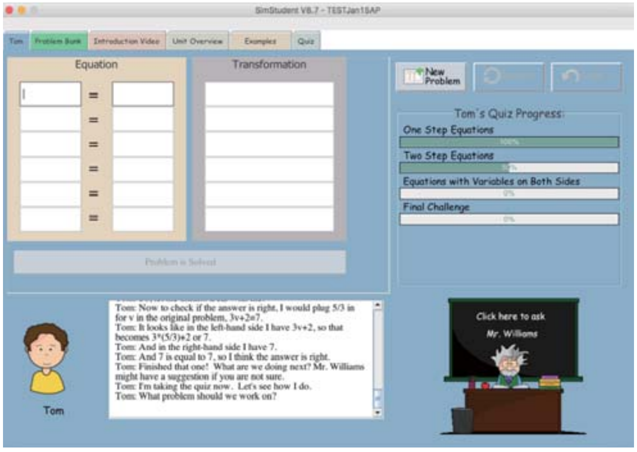

Fig. 1: Example screenshot of APLUS

CogTutor+ (Fig. 2) is designed in such a way that it closely mimics the tutoring behavior of a cognitive tutor—i.e., adaptive problem selection based on knowledge tracing for mastery learning [8]. CogTutor+ is developed to most strictly compare Learning by Teaching and learning by being tutored. The students' goal on CogTutor+ is the same as the traditional Cognitive Tutor, i.e., to reach the predefined mastery level in solving equations.

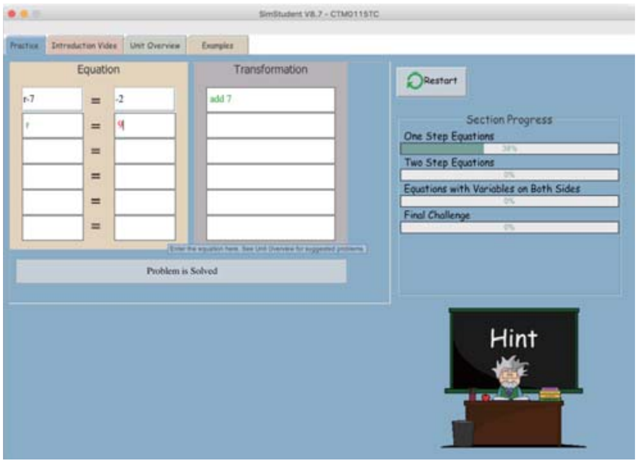

Fig. 2: Example screenshot of COGTUTOR+

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AplusTutor, on the other hand, is designed to control student's goal of learning—i.e., to pass the quiz. Students using AplusTutor select problems by themselves to practice in order to pass the quiz (by themselves). For this reason, we call students' learning on AplusTutor *Self-Regulated Practice*.

The goal of the current paper is to answer two specific research questions: (Q1) Which learning strategy is the most effective? — Learning by Teaching (APLUS), Self-Regulated Practice (AplusTutorr), or Cognitive Tutoring (CogTutor+). (Q2) How do different learning strategies impact students' learning differently? To address these research questions with tight controls, we developed two versions of cognitive tutors that look almost identical to APLUS. We call these cognitive tutors, AplusTutor and CogTutor+.

To answer these two research questions, we tested the following specific hypotheses: (H1) There is no difference on learning outcomes between different learning strategies. Completing the quiz (either by SimStudent or by students themselves) leads to no better learning than achieving the mastery level in cognitive tutoring. However, students in the Self-Regulated Practice condition finish the quiz faster than Learning by Teaching, because the Learning by Teaching condition requires interactively teaching SimStudent, which takes time. (H2) Learning by Teaching students show more improvement on the Conceptual Knowledge Test compared to the other conditions because SimStudent asks "why" questions which builds students conceptual understanding. To test these hypotheses, we conducted a classroom ("in-vivo") study where we compared the three strategies.

2.1 Method and Participants

The study was a randomized controlled trial with three conditions: (1) *Learning by Teaching* (LBT) where students used APLUS. (2) *Cognitive Tutoring* (CT) where students used CogTutor+. (3) *Self-Regulated Practice* (SRP) where students used AplusTutor.

Two public schools participated in the study with the total of 184 students in 12 7th and 8th grade algebra classrooms. In each classroom, students were randomly assigned to one of three conditions (i.e., within-class randomization).

The study ran for six days, one class period (45 to 50 minutes) per day. On the first day, all participants took a pre-test. On the 2nd through 5th day, participants used the software. On the last day, participants took a post-test.

2.2 Measures

We measured learning outcome and learning activity. Students' *learning outcome* was measured with an online (pre- and post-) test that consisted of two parts: a Procedural Skill Test and a Conceptual Knowledge Test.

The *Procedural Skill Test* has three sections: (1) An Equation section with 10 equation problems—2 one-step equations, 2 two-step equations, and 6 equations with variables on both sides. (2) An Effective Next Step section with 2 equation problems that are half solved. Students identify the correctness of each of four operations proposed as a next step. (3) An Error Detection section with 3 equation problems that are solved incorrectly. Students identify the incorrect step and explain their reasoning.

The *Conceptual Knowledge Test* consists of 24 true/false questions—6 items asking about variable terms, 6 about constant terms, 6 about like terms, and 6 about equivalent terms.

Students' *learning activity* was measured using learning process data that showed detailed interactions between a student and the system. The interactions are automatically collected by the system such as problems used for tutoring or practice, solutions entered by the student and the synthetic peer, quiz progress, and hint requested.

3. Results

For the analysis below, we included students who (a) took both pre and post-tests and (b) used the intervention at least for 3 (out of 4) days. There were 84 students (out of 184 in two schools) who met the criteria. Among these students, we excluded 17 students who scored 100% correct in the Equation part of the Procedural Skill Pre-Test. As a consequence, there were 67 students in the analysis: 24 in Learning by Teaching (LBT), 22 in Self-Regulated Practice (SRP), and 21 in Cognitive Tutoring (CT).

3.1 Learning outcomes

Table 1 shows the average test score for all three conditions. A repeated-measures ANOVA for test score as the dependent variable with test-time (pre vs. post) and condition (LBT vs. SRP vs. CT) as independent variables revealed a main effect for test-time for the Procedural Skill Test (PST); $F(1, 64)=15.43$, $p < 0.001$; $d = 0.29$. The condition is not a main effect; $F(2, 64) = .56$, $p = .58$. For Conceptual Knowledge Test (CKT), test-time was not a main effect; $F(1, 64) = 2.36$, $p = 0.13$, nor condition; $F(2,64) = 0.67$, $p = .52$.

Table1: scores. The number in parentheses shows standard deviation. CKT: Conceptual Knowledge Test. PST: Procedural Skill Test.

	CKT		PST	
	Pre	Post	Pre	Post
LBT	0.49(0.23)	0.53(0.22)	0.55(0.27)	0.62(0.22)
SRP	0.48(0.21)	0.51(0.14)	0.48(0.25)	0.56(0.20)
CT	0.43(0.23)	0.47(0.16)	0.54(0.22)	0.62(0.24)
Total	0.47(0.22)	0.50(0.18)	**0.53(0.24)[a]**	**0.60(0.22)[a]**

The data show that students in all three conditions equally improved their performance in solving equations (the PST score). The data also show that students did not improve their competency on the Conceptual Knowledge Test regardless of the learning strategy. The first half of hypothesis H1 (learning achievement) is supported. H2 is not supported.

3.2 Learning process

To test the second half of H1(speed of learning), we compared learning processes across the three strategies. We analyzed process data with a focus on speed to complete a learning goal and the amount of effort required. We operationalized *speed* as the number of days needed to pass the quiz for LBT and SRP and to reach to a mastery level for CT. As there was an error in data collection for the CT, speed to complete was only measured in LBT and SRP. Eight students in LBT passed all quiz levels and 18 in SRP.

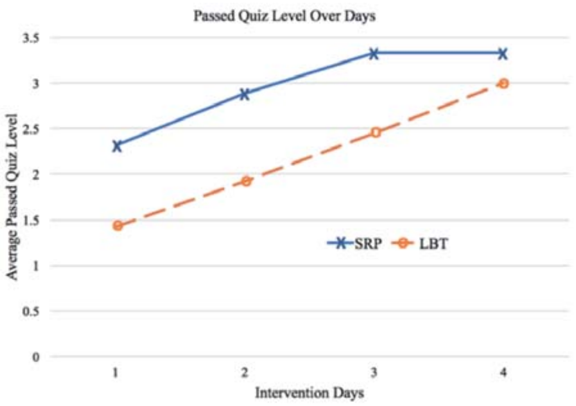

Fig. 3: Transition of quiz levels for Self-Regulated Practice (SRP) and Learning by Teaching (LBT). The X-axis shows intervention days and the y-axis shows the average quiz level passed.

Fig. 3 shows the average quiz level for each intervention day. Figure 3 also shows that SRP students reached higher quiz levels quicker than LBT students. The Learning by Teaching condition plots the quiz level that *SimStudent* passed whereas Self-Regulated Practice plots the one that *students* passed.

The quiz level was operationalized in such a way that One Step Equation is encoded as 1, Two Step Equations as 2, and Equations with Variable on Both Sides as 3. Overall, among all students the average highest quiz level passed was 2.0 for LBT students and 2.8 for SRP students. The difference was statistically significant; $t(60) = 6.18$, $p < 0.001$. These results imply that *students in SRP passed the quiz quicker than SimStudent taught by students in LBT*.

We operationalized *effort* as the number of problems practiced. In the LBT condition, this means the number of problems students entered to teach SimStudent. For the SRP and CT conditions, this is the number of problems that students solved with cognitive tutoring. Fig. 4 shows the number of problems practiced during four days of intervention. The plot shows that CT students practiced on the most number of problems (M=35±11.1) and SRP students practiced on the least number of problems (M=7±7.5). The average number of practice problems for LBT students is 22±8.9.

CT students spent more "effort" on practice than LBT students in terms of the number of practice problems to achieve the same level of learning (measured as the post-test PST score). SRP students spent the least "effort" on practice in all three conditions, but still achieved at the same level of learning.

Fig. 4 also shows that SRP students achieved the same level of learning with a smaller number of practice problems. However, *SRP students spent a considerable amount of time on "editing" their quiz solutions*. Since the system provides corrective feedback on quiz solutions, students knew which step was wrong. They then simply made another attempt on the incorrect step and submitted an "edited" solution. The average number of attempts to submit the quiz was 58.5±6.5 (5.1±1.6 per quiz item). Along with the fact that SRP students practiced 7 problems on average, the data implied that *Learning by Editing (aka Self-Regulated Practice) is as effective as LBT while it requires less practice on solving problems.*

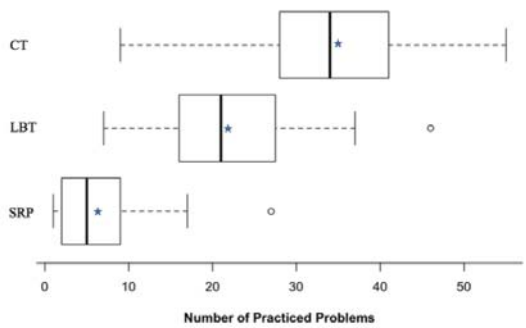

Fig. 4: Boxplot showing the number of practiced problems by students in each condition during the four days of intervention. An asterisk shows a mean.

4. Conclusion

The current study replicated lessons learned from previous studies [5, 6] including the following: (1) Students improved their competency in solving equations by 17% after teaching a synthetic peer on APLUS for four days. (2) The current implementation of APLUS for Learning by Teaching does not necessarily impact students' performance on the conceptual test (Conceptual Knowledge Test in the current paper).

The most important finding from the current study showed no condition difference between Self-Regulated Practice (SRP) and Cognitive Tutoring (CT) in students' learning measured by test scores (both procedural and conceptual tests). This implies that SRP, which is driven by *an intelligent tutoring system without a global student model* (i.e., knowledge tracing), *is as effective as a fully functional cognitive tutoring*. Also, the study showed that SRP and CT are both equally effective as Learning by Teaching.

We found a notable difference in the amount of work students needed to complete in order to achieve the same level of learning. There were no hints available on the quiz in AplusTutor. Therefore, students can enter a failed quiz item into practice and have the cognitive tutor provide scaffolding on how to solve it. As a result, students in our study chose to simply edit solutions most likely on the trial-and-error basis. With VanLehn's terminology [10], this is an "intelligent" tutor without the outer loop for the adaptive problem selection. We call this type of intelligent tutor the Competency Driven Cognitive Tutor (as opposed to the mastery based Cognitive Tutor).

It is not clear why Self-Regulated Practice with a small amount of practice is as effective as LBT. Further studies are required to replicate this finding and validate the results. One concern is about "shallow learning" where students become competent in solving a particular type of problem without deep understanding [11]. To test this hypothesis in a future study, we must measure students' ability on far transfer problems.

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