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Effects of Prior Knowledge in Mathematics on Learner-Interface Interactions in a Learning-by-Teaching Intelligent Tutoring System

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Abstract

This study attempted to determine the influence of prior knowledge in mathematics of students on learner-interface interactions in a learning-by-teaching intelligent tutoring system. One hundred thirty-nine high school students answered a pretest (i.e., the prior knowledge in mathematics) and a posttest. In between the pretest and posttest, they used the SimStudent, an intelligent tutoring system that follows a teaching-by-learning paradigm. The intervention period lasted for three consecutive days with I hour session each. SimStudent captured learner-interface interactions, such as time spent tutoring, number of quizzes conducted, and number of hints requested. It was disclosed that prior knowledge in term identification was the only skill that had a consistent, positive, and significant influence on learner-interface

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interaction with a SimStudent. Thus, the null hypothesis stating that prior knowledge in mathematics does not significantly influence interaction of students with a simulated student was partially rejected. It was concluded that the students may demonstrate or omit a skill, depending on their prior knowledge on identifying the terms of equations and the next step in solving equations. Recommendations and directions for future studies were presented.

Keywords

linear equations, learning-by-teaching, peer tutoring, prior knowledge, simulated student, teachable agent

Introduction

Intelligent tutoring system (ITS) has become popular educational material because of a number of reasons. First, they provide an additional resource for students and teachers (Green, 2011). Second, by means of the ITSs, teachers may provide individualized help that caters to the different tutoring needs of the students (Green, 2011; Marion & Oluwafunmilayo, 2011). Third, students may learn at their own pace (Green, 2011). Finally, the use of ITS may lead to better student academic performance (Chang, 2001; Chien, Yunus, Ali, & Bakar, 2008).

One of the design concepts of the ITS was based on the learning-by-teaching paradigm. In this design concept, the software acted as the tutee while the student served as the tutor or teacher. The software became a teachable agent since it is capable of acquiring the knowledge of the tutor. A teachable agent is "a peer learner that students can teach" (Matsuda et al., 2010, p. 21) and in this situation, the agent uses the acquired knowledge to solve problems in a given domain (Davis et al., 2003). ITS that follows the learning-by-teaching paradigm can prepare the tutors (i.e., students) to teach; thus, resulting to deeper understanding of the materials (Biswas, Schwartz, Bransford, & The Teachable Agents Group at Vanderbilt University, 2001).

Several studies (e.g., Bodenheimer et al., 2009; Kinnebrew & Biswas, 2011; Matsuda et al., 2013) investigated how each interface element of an ITS on learning-by-teaching paradigm contributed to students' academic performance. On the other hand, other studies (e.g., Kinnebrew & Biswas, 2011; Matsuda et al., 2013) described the interaction of a human tutor with a teachable agent that offered an in-depth explanation of the learning gains of a student when tutored by a teachable agent. These studies analyzed the impact of peer tutoring on the academic performance of the student (e.g., between ITS and non-ITS users, between two different versions of the software, or between before and after using the software) or determined the significant predictors of learning in the context of peer tutoring. However, it is still unclear how students' prior knowledge in mathematics influenced their interactions with an ITS which is based on a learning-byteaching paradigm. This study attempted to address this research gap. Toward this goal, it attempted to answer the following questions: (a) What is the mathematics performance of the students before and after the intervention period? (b) How do students interact with the simulated student in terms of time spent tutoring, number of hints requested, and number of quizzes conducted? (c) Does prior knowledge in mathematics influence, singly or in combination, interaction of students with the simulated student?

ITS in Mathematics and Mathematics Performance

Funkhouser (2003) utilized Geometric Supposer in finding the effects of computer software on mathematics achievement and attitudes toward mathematics of secondary school students. Geometric Supposer supports intuitive conjecturing and classification of shapes and properties which was suitable for elementary level students and secondary-school Euclidean Geometry (Center for Educational Technology, 2013). Forty-nine participants were divided into two groups and were distributed evenly according to gender. The experimental group used the Geometric Supposer while the control group was involved in a more traditional geometry instruction. It was shown that members of the experimental group had higher performance on a standardized test of geometry concepts than those on the control group. In terms of attitudes, students who used the software developed a more positive attitude toward mathematics than students who were immersed in the traditional approach.

The use of interactive computer tutorials was implemented in Statistics literacy course. Frith, Jaftha, and Prince (2004) randomly assigned (through students' last names) 67 students to three groups. The three groups used the software on different days within the span of 1 week. The following is the objective of this design:

To explore whether there was any difference in students' learning of the basic concepts of descriptive statistics when they were introduced to the interactive computer tutorials first in the computer laboratory, compared with when they were first introduced to the software in the lecture room. (Frith et al., 2004, p. 4)

It was concluded that computer tutorials were more effective in conveying the statistical concepts than the lecture sessions (Frith et al., 2004).

A computer-assisted system named MathCAL was utilized to determine its effectiveness in improving the performance of 130 fifth-grade students (aged 11 years) on elementary school mathematical problems (Chang, Sung, & Lin, 2006). The software was designed based on four problem-solving stages: understanding the problem, making a plan, executing the plan, and reviewing the solution.

Students were randomly assigned to the groups "not using the computer-assisted problem-solving system" (i.e., the control group) and "using the computer-assisted problem-solving system" (i.e., the experimental group). The students in the experimental group practiced using MathCAL while the control group solved problems on paper. The experiment spanned for 6 weeks, and pretest and posttest were gathered during the experiment. MathCAL was found to be effective in improving the performance of students with lower problem-solving ability. It is also interesting to note that this study reported the learner-interface interactions, such as number of problems practiced, average number of steps for each problem, highlighting, use of calculators, referring to correct answers, and constructing the solution tree. However, no further analysis was done on the data.

The study of Chien et al. (2008) explored the effects of using a computer-aided instruction (CAI) followed by the use of an ITS (CAI + ITS) and by using CAI alone on the performance of students in the topic algebraic expression. Chien et al. (2008) assigned one group of 32 students to study algebraic expression in a CAI learning environment, while the other group of 30 students was in a CAI + ITS environment. Pretest was administered before the start of the experiment and posttest was given after the 8-hour session of using the software. The results of the study showed that there was a significant difference in the students' solving algebraic expression between students who used CAI + ITS than those who used CAI alone. Thus, the researchers concluded that CAI + ITS was more effective in helping students learn algebraic expression as compared with using CAI alone.

Pareto, Haake, Lindstrom, Sjoden, and Gulz (2012) utilized an educational game in mathematics which was based on teachable agent model. The researchers studied the impact of the said software in terms of conceptual understanding and attitudes toward mathematics. The study revealed that the math comprehension of students in the experimental group (i.e., 19 students that used the software) increased significantly than those in the control group (i.e., 19 students under regular instruction), but there was no significant difference in terms of attitude change.

Matsuda, Cohen, Sewall, Lacerda, and Koedinger (2007) developed a simulated student (SimStudent) that acted as tutee that a human student could tutor. The student tutor gave SimStudent a problem to solve. SimStudent then attempts to solve the problem one step at a time. Occasionally, it would ask students about the correctness of each step. If it cannot perform a step correctly, it asks the student for a hint. The student has to demonstrate the step as a response to the hint. It was shown that when trained on 20 problems, SimStudent could accurately predict students' correct behavior on the mathematics problems more than 82% of the time. To test how well SimStudent learned the material, the student tutor gave SimStudent a quiz. The quiz has four parts, all of which SimStudent must pass. If SimStudent fails one part, SimStudent may not proceed to the next part of the quiz. Matsuda et al. (2012) further studied the effects of tutor learning after using SimStudent. The SimStudent in this study had two versions: The first version solicited explanation from the tutors while the second version was a non-selfexplanation type. The first version enabled SimStudent to occasionally ask question such as why the student opted to solve the input problem, an explanation of a solution step, and algebraic terminology reinforcement. Self-explanation could help students reflect on their own learning and refine their understanding of a concept.

The second version lacks these capabilities. The number of problems and self-explanations provided by the tutors were logged and analyzed. One hundred sixty students participated in the study. A pretest was administered before the intervention period. The intervention period lasted for three class days. During this time, students tutored the SimStudent. After the intervention period, students took the posttest. The examination consisted of procedural tests (e.g., equation solving, next step, and demonstration of errors) and conceptual test (e.g., variable or constant identification and equivalent expressions). It was shown that students who used the non-self-explanation version of the software completed more problems than those who used the self-explanation version (Matsuda et al., 2012). It was revealed that there was a weak effect of the software on procedural skill acquisition. Further, even with the self-explanation, the system did not help students learn conceptual knowledge.

In a recent study, Matsuda et al. (2013) reported that the software was effective for learning procedural skills but not for learning conceptual knowledge. It was shown that there was a significant correlation between tutee and tutor learning, that is, students tended to learn more when they tutored SimStudent correctly (i.e., with an accurate response) and appropriately (i.e., on appropriate problems with a sufficient amount of explanations).

Prior Knowledge and ITS

Rodrigo et al. (2013) investigated the cognitive factors that predicted learning gains after using the SimStudent. In this article, tutoring interactions and test scores were analyzed to understand what made learning-by-teaching more effective. The study was conducted at two separate locations. The first study locale was at a high school in Pittsburgh, PA, USA. There were eight Algebra I classes with an average member of 20 students per class. A total of 160 students with age ranging from 14 to 15 participated in the study. The second research locale was at a laboratory high school of one of the universities in the University Belt in Manila. There were 201 participants in the said research locale with age ranging from 11 to 15. The study revealed that prior knowledge had a strong influence on tutor learning. It was also shown that if students did not have sufficient prior knowledge for tutoring, they would not benefit from tutoring

as much as students who had appropriate prior knowledge. Moreover, regression analysis disclosed that prior knowledge was the dominant predictor of posttest scores for the procedural skill test.

In the two studies conducted by Matsuda et al. (2013), they showed that prior knowledge of tutee and tutor affected the learning of the tutor. Specifically, prior competence of the tutor on procedural skills and conceptual knowledge were both predictive of students' posttest scores on the procedural skills test. The first study utilized a self-explanation of SimStudent, while the second used a SimStudent with a game feature (i.e., students compete with one another). There were 81 and 69 participants for the first and second studies, respectively.

Chen and Huang (2013) examined how prior knowledge influenced the reaction of 81 students to two different types of two game-based learning systems (i.e., the Machinarium and CSI: Web Adventures). The former delivered procedural knowledge (i.e., problem-solving skills in the form of solving puzzles), while the latter was focused on the declarative knowledge (i.e., knowledge about forensic science). Prior knowledge referred to the students' previous understanding of the subject content delivered by game-based learning as well as level of experience with digital games. It was shown that prior knowledge was useful for declarative knowledge but not for procedural knowledge.

Meanwhile, Winters, Greene, and Costich (2008) argued that computerbased learning environments may provide learners with multiple representations and opportunities; it was up to the learners to determine which of the representations were most helpful based on their self-knowledge, beliefs, motivation, task definitions, goals, strategic knowledge, and prior knowledge. This was supported by the study of MacGregor (1999). It was found out that middle school students with higher prior knowledge on Science had higher internal locus of control or self-regulation, connected more concepts as they navigated in a hypermedia environment, had higher need for cognition, and had higher scores on the learning measure than those with lower prior knowledge.

Moreover, Moos and Azevedo (2008) showed that prior domain knowledge was related to how participants self-regulated their learning task with hypermedia. Further, it was positively related to the monitoring and planning of participants while it was negatively related to their use of strategies during the hypermedia learning task. The authors explained that students with high prior domain knowledge indicated that they had well-established, interconnected knowledge base of the topic that allowed them to engage in "knowledge verification." On the other hand, students with low prior domain knowledge were engaged on what the researchers called "knowledge acquisition." The lack of students' prior knowledge regulated their learning by note-taking and summarizing the topics on the hypermedia environment.

Synthesis of Literature Review

ITSs provided students alternative educational materials. The literature provided evidence that students learned from these educational materials. It was also shown that ITSs were capable to teach the students new skills or to enhance their existing skills. To fully optimize the power of ITS, researchers investigated how prior knowledge influenced learning of students. However, the existing literature failed to uncover how students would exhibit their skills during an interaction with an ITS. This is considered important since it would give researchers and educators an understanding on how students exhibit their skills during an interaction with a simulated student. This study attempted to fill in this research gap.

Research Paradigm and Hypothesis

In this study, it attempted to determine the influence of prior knowledge in mathematics on the interaction of the students on a simulated student. Prior knowledge in mathematics was measured in terms of skills in equation solving, term identification, next step, equivalent expression, and error identification. These were the indicators of the independent variables (IVs). The dependent variable was learner-interface interactions which was measured in terms of time spent tutoring, number of quizzes conducted, and number of hints requested. It is hypothesized that prior knowledge in mathematics does not significantly influence interaction of students with a simulated student. The research paradigm is shown in Figure 1.

Methodology

Research Design, Locale, and Subjects

This descriptive study was conducted at the Elementary and Secondary Laboratory School (ESLS) of a university in Manila. The study aimed to determine how prior knowledge in mathematics could influence the interaction of the students with a simulated student. Toward this goal, participants of the study were involved in a 3-day intervention period. Each session of the period lasted for an hour. The intervention period could not be extended because of time constraints (e.g., students had other classes with other subjects, quizzes with other classes, and time allotment to extracurricular activities). Before and after the intervention period, tests were administered. The tests and the intervention period were discussed in details in the succeeding section.

The respondents of the study were first year high school students who took up Introductory Algebra. There were 236 students during the school



Figure 1. Research paradigm of the study.

year 2011–2012. All of them participated in the study. Hence, there was no sampling method applied. However, only 139 (59%) students who completed the test examinations and the 3-day intervention period were considered in the study. The average age of the participants was 13 years. There were 50 female and 89 male participants.

Data Gathering Procedure and the Research Instruments

There were two sets of data gathered in the study. The first set of data was on the performance of the students on Introductory Algebra with a specific topic on linear equations. Linear equations are in the form of ax + b = c, where $a \neq 0$, for example, 3x + 5 = 2. It was chosen as the focus of the study because of two reasons. First, it is one of the fundamental topics in Algebra. Second, higher mathematics required extensive and appropriate skills on the said topic. Pretest and posttest were administered to determine the performance of the students. Pretest was used to determine the prior knowledge of students in mathematics.

There were three versions of tests—Test A (α -pretest = 0.92; α -posttest = 0.92), Test B (α -pretest = 0.91; α -posttest = 0.94), and Test C (α -pretest = 0.95; α -posttest = 0.95). The three tests had the same topics but each topic had different given problems with the same level of difficulty. The test questions were adapted from Matsuda et al. (2012). The tests have high Cronbach's alpha (α) values (alpha values of at least .90) which indicated high reliability of the test questions. The content of the tests was content validated by three high school algebra teachers of the ESLS. The three high school Algebra teachers agreed that the questions were appropriate to the level of students and to the Introductory Algebra curriculum.

The tests were assigned to students at random. Equal number of students was assigned to each type of test and students did not take the same test version twice. It must be noted that the test was a right-minus-wrong type of examination. For every wrong answer, a negative one point was given. Nonetheless, no deduction was given if the student opted not to answer the question or

ltems	Number of items
Procedural tests	
Equation solving	10
Error identification	5
Next step	12
Conceptual tests	
Equivalent expression	10
Term identification	38
Total	75

Table I		Research	Instrument.
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responded by stating "Not Sure." This was intended to deter students from guessing the answers. Nonetheless, this was not carried out in counting the scores.

The tests involved five parts—Equation Solving, Term Identification, Next Step, Equivalent Expression, and Error Identification. The items of each part are shown in Table 1. Equation Solving, Next Step, and Error Identification involved procedural knowledge of algebraic linear equation. On the other hand, Term Identification and Equivalent Expression were part of the declarative knowledge of algebraic linear equation. Equation Solving had 10 linear equations to be solved by the students. Term Identification (i.e., identification of a constant, variable, and like terms in a given expression) had 38 questions which could be answered with a true or false. Next Step was the part of the test where students determined whether the next step in the solving an equation was appropriate or not. There were 12 questions under this category which could be answered with agree or disagree.

Ten true-or-false items were allotted for Equivalent Expressions (i.e., mathematical expressions whose values are the same for any value substituted in both expressions). Lastly, there were five questions in Error Identification. In this section, students identified which of the steps in the computation was incorrect and they were also required to explain why that step was incorrect. There were 75 questions all in all.

The test results were converted to percentages. Equation (1) was used to get the percentage. This was based on the grading policy system of the University. Scores were converted to percentages and were given to the teachers of the participants.

$$Percentage = \frac{Student's \ score}{Highest \ possible \ score} \times 50 + 50$$
(1)



Figure 2. Stacy (A simulated student) (a) attempting to solve a problem, (b) solving the equation on its own, (c) notifying the tutor that it had finished solving the problem, and (d) on quiz mode.

Data gathering was administered in a period of three consecutive days. Each period ran for 1 hour. Pretest was administered on the first day of the 3-day period. Before pretest, students had only an idea about simple linear equations. For the following three consecutive days, students tutored the SimStudent named Stacy (see Figure 2). SimStudent was utilized in this study because it provided online log repository and data analysis. Further, content of tests administered in SimStudent study were similar to the ones in the Filipino high school syllabus. This was the intervention period. Afterwards, posttest was administered. During these periods, there was no teacher intervention since the topics were not yet introduced to the students.

The second set of data was composed of interaction of the students with the SimStudent. At the intervention periods, logs were gathered. During this period, the student (the tutor) gave SimStudent, named Stacy, linear equation problems. Stacy would try to solve the problem one step at a time and would occasionally ask the tutor if the step taken was correct or not (see Figure 2(b)). The tutor responded by clicking the Yes or No button. If Stacy could not provide a step, she would ask the tutor for a hint, where the tutor must demonstrate the necessary step. Time spent tutoring and request for hints were captured in tutoring mode (Figures 2(a)–(c)), while the number of quizzes conducted was gathered in quiz mode (Figure 2(d)).

Stacy (the tutee) and the student (the tutor) could work collaboratively on solving a problem. For example, the tutor inputs the equation "3x - 6 = 8" (Figure 2(a)). Stacy would attempt to solve the equation on her own and asks the tutor if every step she takes is correct or not (see Figure 2(b) and (c)). The tutor would input his or her response to the "Submit" textbox with "Yes/No" response. If the step is incorrect, Stacy would ask the tutor to type-in the step at the equation and transformation boxes. The process will continue until the problem is solved. Stacy would notify the tutor that it had finished solving the problem (see Figure 2(c)).

Stacy could not distinguish if the feedback and demonstration provided by the tutor was correct. Thus, Stacy could acquire skills provided by the tutor, regardless of whether the skill was based on correct or incorrect learning. The tutor could measure Stacy's learning by enabling the Quiz function (see Figure 2(d)). The Quiz interface was similar to the tutoring interface except that no feedback could be provided by the tutor. In quiz mode, Stacy would randomly select quizzes from its database. Then, Stacy will solve the equation on her own and does not require responses from the student. In other words, Stacy solves the problem on its own in the Quiz interface. Consequently, the student would just look at the process how Stacy solves a problem.

The tutor's activities during the intervention sessions were stored in Stacy's database. All log data were sent to an online open data repository called DataShop. Included in these recorded activities were time spent tutoring, requests for hints, and quizzes conducted. Time spent tutoring was recorded in milliseconds. Hints were measured in terms of number of times the tutor sent a hint to answer a problem. Quizzes conducted were the number of quizzes requested by the tutor to the tutee. It must be noted that no assistance to the respondents was provided in solving the problems. In this manner, the integrity and reliability of the data collected were ensured. It must be noted that

- 1. prior knowledge was measured using a pretest;
- 2. time spent tutoring refers to the actual time used by the students in tutoring the SimStudent; and

3. time spent in the quizzes was eliminated to avoid multicollinearity of the variables.

Parental consents were secured before proceeding with the study. Furthermore, students were not forced to use the software even when parental consent was secured. Mean and percentage were utilized to describe the data. Regression analysis was employed to determine the influence of mathematics prior knowledge on learner-interface interactions with a simulated student. Prior to regression analysis, collinearity statistics and Q-Q plot analyses on the IVs were employed. The IVs exhibited normal distribution except that Error Identification was skewed to the right. Nonetheless, all IVs exhibited linear relationship. Moreover, the Variance Inflation Factors (VIF) of the IVs—VIF(Equation Solving)=1.07; Identification) = 1.23; VIF(Next VIF(Term Step) = 1.14;VIF(Equivalent Expression = 1.27; VIF(Error Identification) = 1.04—were lower than the 3.0 threshold (Hair, Black, Babin, & Anderson, 2010). It was shown that multicollinearity did not exist among the variables. Thus, the researchers proceeded with regression analysis. A .05 level of significance with 95% reliability was adopted to determine the significance of the findings.

Findings

Performance of the Students in Introductory Algebra Before and After the Intervention Period

Table 2 presents the pretest and posttest results. The average performance of students in the pretest and posttest was 63% and 64%, respectively. The overall mean was 64. Error Identification had the lowest average throughout the type of tests (Pretest Mean = 51; Posttest Mean = 53). Meanwhile, Term Identification (Pretest Mean = 72; Posttest Mean = 73) was consistently found to have the highest means throughout the types of test.

Students Interaction With Simulated Student and Influence of Prior Knowledge in Mathematics on Students Interaction With Simulated Student

Table 3 shows the learner-interface interactions of the students. Students spent 36.2 minutes per session on tutoring Stacy. On the average, students posted nine quizzes per session. Further, the average number of request hints per session by the tutee was 15 hints.

Tables 4 to 6 show the regression of learner-interface interactions with students' mathematics prior knowledge. Table 4 shows that prior knowledge in term identification (beta = 0.33, p < .05) positively influenced time spent tutoring. Further, next step influenced negatively time spent tutoring (beta = -2.20,

	Types of test		
Topics	Pretest mean	Posttest mean	
Procedural tests			
Equation solving	56	57	
Error identification	51	53	
Next step	68	68	
Conceptual tests			
Equivalent expression	69	67	
Term identification	72	73	
Overall mean	63	64	
Grand mean	(64	

Table 2. Performance of the Students During Pretest and Posttest.

Table 3. Learner-Interface Interaction Results.

Results	Mean
Time spent tutoring	36.2 minutes
Number of quizzes conducted	9 quizzes
Number of hint requests	15 hint requests

Table 4. Regression of Time Spent Tutoring on Mathematics PriorKnowledge.

Mathematics prior knowledge	Beta	Þ
Equation solving	0.02	.802
Term identification	0.33	.000
Next step	-2.20	.019
Equivalent expression	0.01	.917
Error identification	-0.0I	.874

Adj. $R^2 = 0.11$, F(2, 136) = 9.20, Sig. = .000.

p < .05). Both predictors were accounted for 11% of the variability in the spending time tutoring the simulated student. The result of the regression was unlikely to have arisen from sampling error, F(2,136) = 9.20, p < .05.

Regression of learner-interface interactions in terms of number of quizzes conducted on mathematics prior knowledge is shown in Table 5. A mathematical skill

Mathematics prior knowledge	Beta	Þ
Equation solving	0.089	.304
Term identification	0.23	.007
Next step	-0.12	.150
Equivalent expression	-0.09	.349
Error identification	0.002	.983

 Table 5. Regression of Number of Quizzes Conducted on Mathematics Prior

 Knowledge.

Adj. $R^2 = 0.05$, F(2, 136) = 7.59, Sig. = .000.

Table 6. Regression of Number of Hints Requested on Mathematics PriorKnowledge.

Mathematics prior knowledge	Beta	Þ
Equation solving	0.001	.995
Term identification	0.18	.035
Next step	-0.13	.135
Equivalent expression	0.03	.725
Error identification	-0.10	.250

Adj. $R^2 = 0.03$, F(2, 136) = 4.53, Sig. = .035.

in term identification predicted positively (beta = 0.23, p < .05) the number of quizzes that a student would conduct in an ITS. The Adjusted R^2 showed that 5% in the variation of number of quizzes given to the simulated student was attributed to the prior knowledge in term identification. The regression result was unlikely to have arisen from sampling error, F(2,136) = 759, p < .05.

Term identification predicted positively the number of hints by the SimStudent (beta = 0.18, p < .05). It can be ascertained that the result was not due to sampling error, F(2,136) = 4.53, p < .05. Three percent of the variation of the numbers of hints requested was due to previous knowledge in identifying terms in a linear equation.

Discussion

Performance of the Students in Introductory Algebra Before and After the Intervention Period

Table 1 shows that students had difficulty on Error Identification throughout the types of test. The results indicated that the performance of the students in this

topic was low. In Error Identification, students had to identify what made the computations incorrect and they had to give reasons why the computations were incorrect. This shows that the tasks of identifying the error in the computation and giving the reason(s) of committing the error in the computation are difficult tasks for students who are learning basic algebra. This was quite understandable since this task involved mastery of the subject matter. The result serves as a note to teachers that students who are on the beginner stage of learning linear equations may find this skill difficult. Teachers are advised to focus their discussion on this skill and give reasonable points (e.g., about 10% of the total questions) when conducting a quiz. The result also supports the study of Matsuda et al. (2012, 2013) and Rodrigo et al. (2013) that only few questions on this skill set should be given during their tests administration.

Meanwhile, term identification was consistently found to have the highest means throughout the types of test. These were found to be the highest means throughout the topics and types of test. This topic covered the identification of algebraic terms in an equation. The questions under this topic could be answered by "true" or "false." Relatively, students performed better in this topic since the nature of the topic and the manner it could be answered made this topic easiest. This explained why students got the highest mean percentage in term identification.

Meanwhile, it was observed that students exhibited an interesting behavior while conducting the pretest and posttest. During the pretest, students were cautious in answering the test since they were aware of the test instructions. After the intervention period, it was observed that students became more confident in answering the posttest examination than when they were answering the pretest. Students opted to answer more questions in the posttest than the pretest despite the fact that they knew the consequence of having wrong answers. Thus, it can be deduced that students' behavior might change after using an ITS, and it could be carried on the actual test. Students perceived that they had taught Stacy well and they also thought that they would perform well in the test. Consequently, it had an effect on the performance of the students.

There are emerging questions that need further investigations from this finding. Given that students' performance did not improve significantly after a 3-hour session, would it improve if the intervention would be extended? How many tutoring session hours are needed to reach a passing mark? In the same manner, could it affect students' information retention? Would it also reach the point where tutoring the simulated student would no longer contribute to the performance of the students? If so, how many session hours would it take? Further studies could be conducted to answer these questions.

Students Interaction With Simulated Student and Influence of Prior Knowledge in Mathematics on Students Interaction With Simulated Student

The findings in Table 3 show that the average time students spend in tutoring the intelligent agent was only a little over half an hour. It must be noted that the participants of the study were from the high school building. Thus, the remaining 23.8 minutes was devoted to travel time from the high school building to the computer laboratories and to logging on to computers. Nevertheless, even the students had only a short duration of time spent in tutoring the intelligent agent, they managed to post nine quizzes per session and the average number of request hints by the tutee was 15 hints. These parameters indicate that students were eager and engaged to participate in the study.

The predictors of learner-interface interactions in a learning-by-teaching tutoring system were determined through regression analysis. The results are shown in Tables 4 to 6. As shown in Table 4, term identification positively influenced time spent on tutoring. This indicates that as students have higher knowledge in identifying terms in linear equation, it can be expected that the amount of time interacting with a SimStudent will be higher. As students become more proficient in this skill, students will be more able of tutoring the SimStudent. This finding can be explained by the fact that term identification is the fundamental skill in linear equation. This skill involves classification of terms in an algebraic linear expression as a variable, a constant, or like terms. A student with strong background on this skill can identify similar terms easily and can manipulate them mathematically. In other words, proficiency in term identification leads to other mathematical skills.

On the other hand, next step had a negative influence on time spent tutoring the SimStudent. Next step involves identifying the subsequent correct steps in solving a linear equation. It was shown that time spent tutoring would decrease by 2.20 units for every one unit increase in next step. This finding offers a vivid role of prior knowledge on learner-interface interactions. The result suggests that as students become more competent in identifying the correct steps in solving an equation, it can be expected that the time spent tutoring will decrease. This is because students may skip steps in solving an equation; thereby, diminishing the number of hours spent in tutoring. For example, a beginner in linear equation may solve the equation -5 + 4x = -17 - 2x with six or more steps, whereas a more experienced one may only involved three steps.

Prior knowledge in term identification had positive effects on number of quizzes conducted. In conducting quizzes, Stacy would solve an equation on its own. Students would simply watch how Stacy solved a problem. With prior knowledge in term identification on hand, students would attempt to determine the pattern and strategies of the SimStudent in solving linear equations. They would want to understand how the SimStudent manipulated the terms,

variables, and numbers in solving an equation. In fact, during the experiment, it has been observed that students were switching from the tutoring module to quiz module and vice versa. This behavior can be explained by the fact that giving quizzes to the SimStudent mimics a classroom measurement on how much the student learned from the topic. In the context of this study, SimStudent quizzes were actually reflections on how much the tutor learned from the tutoring process. Therefore, this learner-interface interaction was a means of confirmation whether the tutor learned a correct mathematical skill.

Prior knowledge in term identification positively predicted the number of hints requested. Hint request is a form of soliciting-skill interface from the tutor. As shown in Figures 2(a) to (c), the tutee would ask which of the terms had to be manipulated. In the equation 3x - 6 = 8, Stacy asked the tutor if adding 6 both sides would be an appropriate (i.e., correct) move. The operations were fixed (e.g., addition, subtraction, multiplication, and division) but the terms to work on might vary. Therefore, this learner-interface interaction was grounded on the correct term identification.

It is interesting to note that this study offers a vivid contribution to the SimStudent research. Previous SimStudent studies showed promising results. Matsuda et al. (2012) showed that SimStudent had weak effect on procedural skill. In 2013, Matsuda et al. revealed that students learned when they tutored SimStudent with correct response and appropriate problems. Similarly, Rodrigo et al. (2013) disclosed that sufficient prior knowledge for tutoring was needed so that students may benefit from the tutoring process. This current study contributed to these existing threads of SimStudent studies by showing that prior knowledge may influence how students interact with a simulated student during the tutoring process.

In previous studies like that of MacGregor (1999) and Moos and Azevedo (2008), they showed that different levels of prior knowledge of learners may verify or acquire the contents of hypermedia. In this study, it was shown that the relation of prior knowledge in mathematics to the interaction of the students in an ITS based on learning-by-teaching paradigm can either be "skill demonstration" or "skill omission." The first skill allows students with prior knowledge in term identification to engage them positively in tutoring and to provide a venue to exhibit their problem-solving skill. To this end, SimStudent achieved its goal. On the other hand, higher levels of skill in identifying the next step in solving mathematics problems may permit the students to skip steps in solving problem which, in turn, would reduce the time spent in tutoring.

Moreover, it was disclosed that term identification was a consistent predictor of all learner-interface interactions with a simulated student. The implications of the findings are threefold. First, it is an indication that at least one prior knowledge of the skill sets can engage students in peer tutoring. Second, even though students had low prior knowledge in term identification, it was not an obstacle to get involved in tutoring. Lastly, while the other skills are equally important, the finding suggests that students must have a strong background on term identification before proceeding to other skill sets.

Conclusions and Recommendations

On the basis of the findings presented earlier, the null hypothesis stating that prior knowledge in mathematics does not significantly influence interaction of students with a simulated student is partially rejected. It can also be concluded that prior knowledge in mathematics influenced interaction with the tutoring system either as a form of "skill demonstration" or "skill omission."

There are possible future studies identified through the course of the study. It is observed that students' behavior tends to change toward answering an examination after using the software. An in-depth study may be initiated to understand this phenomenon. There are interesting research gaps in terms of usage of the SimStudent that are worth investigating. These are (a) to determine if students would achieve a passing mark if the use of the software is extended, (b) to find out how long would it take to achieve a passing mark, and (c) to find out at what point would the software no longer contribute to the students' learning.

Future studies may also include the quality of the hints and quizzes (i.e., correct or incorrect hint, helpful or not helpful hint, and correct quiz; Matsuda et al., 2013). It is also recommended that the number of hours of the intervention period be extended. It is also suggested that students be encouraged by the experimenters to tutor the simulated students with different problems. Finally, it is suggested that the experiment be redesigned to ensure optimal learning from the software.

Limitations

The predictive powers of the regression models imply that the experiment had inherent limitations. The study did not consider participants' demographics, learning styles, motivations, mathematical ability skills, and attitudes or behavior toward mathematics that might have influenced the results of the study. It must be emphasized that the participants of the study are non-native English speakers. SimStudent does not provide multilingual capabilities. Hence, participants might be unfamiliar to the tutoring approach and the overall appearance of the software. For example, students are more familiar with the concepts of transposition than by adding or subtracting terms on both sides. Finally, the design of the experiment primarily influenced the findings of the study.

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