

Running Head: ALEKS AFTER-SCHOOL IMPLIMENTATION

The impact of a Technology-based Mathematics After-school Program using ALEKS on Student's
Knowledge and Behaviors

Scotty D. Craig¹, Xiangen Hu², Arthur C. Graesser², Anna E. Bargagliotti³, Allan Sterbinsky²,
Kyle R. Cheney², & Theresa Okwumabua²

¹Arizona State University, Polytechnic
Mailing address: 7271 E Sonoran Arroyo Mall, Santa Catalina Hall, Ste. 150, Mesa, AZ 85212
Phone: 480-727-1006
Email: Scotty.Craig@asu.edu

²University of Memphis

³Loyola Marymount University

Craig, S. D., Hu, X., Graesser, A. C., Bargagliotti A. E., Sterbinsky, A., Cheney, K. R., &
Okwumabua, T. (in press). The impact of a technology-based mathematics after-school program
using ALEKS on student's knowledge and behaviors. *Computers & Education*.

Corresponding author: Scotty D. Craig, scotty.craig@asu.edu

Abstract: The effectiveness of using the Assessment and LEarning in Knowledge Spaces (ALEKS) system, a Intelligent Tutoring System for mathematics, as a method of strategic intervention in after-school settings to improve the mathematical skills of struggling students was examined using a randomized experimental design with two groups. As part of a twenty-five week program, student volunteers were randomly assigned to either a teacher-led classroom or a classroom in which students interacted with ALEKS while teachers were present. Student's math performance, conduct, involvement, and assistance was needed to complete tasks were investigated to determine overall impact of the two programs. Students assigned to the ALEKS classrooms performed at the same level as students taught by expert teachers on the Tennessee Comprehensive Assessment Program (TCAP), which is given annually to all Tennessee students. Furthermore, student's conduct and involvement remained at the same levels in both conditions. However, students in the ALEKS after-school classrooms required significantly less assistance in mathematics from teachers to complete their daily work.

Highlights:

Interacting with ALEKS after school is as effective as interacting with expert teachers.
Student behavior was equivalent for both ALEKS and teacher after-school classrooms.
ALEKS after-school students needed less help than teacher taught after-school students.

Acknowledgement

This research was supported by the Institute for Education Sciences (IES) Grant R305A090528. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of IES (DOE).

The Impact of a Technology-Based Mathematics After-school Program using ALEKS on Student's Knowledge and Behaviors

1. Introduction

1.1. Overview of Need

Reports and research studies (National Center for Education Statistics, 2008; National Mathematics Advisory Panel, 2008; Dynarski, Agodini, Heaviside, Novak, Carey, Campuzano, et al., 2007) have found that simply incorporating technology into classroom settings does not provide a significant improvement. If Dynarski et al. is correct, current learning technology has very little value added when implemented into classrooms. It is plausible that replacing students' time in classrooms may not be the most effective use of technology for learning. Other settings such as after school could provide potentially valuable options for implementation. However, it is still unclear how these technologies will compare against standard teacher-led after-school programs or if the decreased human interaction will cause more behavioral problems in the afterschool setting.

1.1.1 Opportunities of after-school settings

After-school settings provide an excellent time frame for the use of technology. This additional time devoted to academic training of knowledge and skills can be a learning opportunity for students in any subject matter and regardless of type of learning environment (Gayle, 2004; Kugler, 2001; Miller, 2003). However, this time is often underutilized with only around 11% of students participating in after-school programs (Kanter, 2001) with the students that are most in need the programs not participating (Cross, Gottfredson, Wilson, Rorie, & Connell, 2009; Dearing, Wimer, Simpkins, Lund, Bouffard, Caronongan, 2009). However, when the performance of students that attend after-school programs to those that do not, the students

attending the after-school programs tend to outperform their peers not participating in after-school programs academically both in classrooms (Vandell, 2007) and on state mandated standardized tests (Hu, Craig, Bargagliotti, Graesser, Okwumabua, Anderson, et al., 2012).

Research confirms that after-school programs have shown positive effects for mathematics knowledge (Fashola, 1998; Hu et al. 2012; Jackson, 2011; Lauer, et. al., 2006; Pierce, Bolt, & Vandell, 2010) and perception the importance of mathematics (Jackson, 2011). Vandell (2007) noted sixth and seventh grade students who regularly attended after-school programs scored 12 percentile points better in mathematics than their peers. These results were again confirmed by a meta-analysis by Lauer et al. (2006), who reported that it was after-school programs that applied one-on-one tutoring techniques that displayed the greatest gains. However, the effects of after-school programs are often murky because attendance in the programs tends to be sporadic and many students view the programs as additional school time (Vandell, Reisner, Brown, Dadisman, Pierce, Lee & Pechman, 2005).

1.1.2 Student behavior in classroom and after-school settings

It has been well documented that standard classroom students tend to be inattentive to learning tasks during class or even exhibit openly disruptive behavior (Finn, Fulton, Zaharias, & Nye, 1989; Finn, PannoZZo, & Voelkl, 1995). Further, these behaviors have been observed to have a negative impact on classroom learning (Finn et al., 1995; Seidman, 2005; Swift & Spivack, 1968). One example of inattentive task behavior comes from Petterson, Swing, Stark, and Waas (1984). They found a significant relationship between 5th grade students' reported attention level and if they were actively processing the material during mathematics course and mathematics achievement test scores(i.e. the less engaged a student reported being in a task, the worse the student performed).

Disruptive behavior can be more harmful to learning than inattentive behavior, because it impacts the entire classroom distracting other students from learning and demanding teachers instructional time (Finn et al., 1995). It has also been shown that disruptive behavior has a *contagion effect* where by a disruptive act by one student normally followed by disruptive acts by other students (Spivack & Cianci, 1987). However, the same incidence of disruptive behavior is not observed in after-school settings (Beck, 1999). This might have to do with the setting itself. In that, small class sizes that provide more attention from teachers have shown fewer instances of inattentive behavior and disruptive behavior (Achilles, 1999; Bourke, 1986; Finn, 2003).

It is still an open question as to the impact that learning technology could have on student behavior in afterschool settings. However, teachers ratings of behavioral problems have been seen to decrease with the implementation of technology such as projection board (Parette, Stoner, et al., 2009), personal laptops in the classroom (Righi, 2012) and Computer-Assisted Instruction (Mazzoti, Wood, Test, & Fowler, 2012) when compared to standard classrooms.

1.2. Intelligent Tutoring Systems and computerized learning systems

While Dynarski et al. (2009) brought into question if technology's integration in the classroom was effective, technology has been shown to have a positive impact on student learning in mathematics. Schacter (1999) reviewed over 700 empirical research studies in which students had exposure to computer-assisted instruction. The students showed overall positive gains in achievement on tests that spanned researcher-conducted tests, standardized state tests, and national tests. Regarding the intelligent tutoring systems (ITS), the effect sizes on experimenter-developed tests in assessments of intelligent tutoring systems are approximately 1.0 sigma compared to normal classroom teaching (Corbett, 2001). A meta-analysis of the tutoring

literature found a Cohen's d effect size of .76 versus .79 for human tutors suggesting that an ITS could be just as effective as one to one human tutoring (VanLehn, 2011). According to Ritter et al. (2007), standardized tests show overall effect sizes of 0.3 sigma in assessments in hundreds of classrooms, but perform particularly well for the subcomponents of problem solving and multiple representations, which show effect sizes of $d = 0.7$ to 1.2. The *What Works Clearinghouse* investigations show an effect size of 0.4 sigma (Ritter et al., 2007). These large scale efforts present an optimistic picture of the role of technology in mathematics learning. These findings have helped inspire the development of commercial technologies that target mathematics, such as MyMathLab (Pearson, 2011), and sophisticated intelligent tutoring systems, such as the Cognitive Tutors developed at Carnegie Learning (Heffernan, Koedinger, & Razzaq, 2008; Ritter, Anderson, Koedinger, & Corbett, 2007).

Nevertheless, the research on using technology to improve performance in mathematics has provided some mixed results when evaluated in the K–12 grades. Dynarski et al., (2007) reviewed software products for first grade reading, fourth grade reading, sixth grade math, and algebra finding no significant test score differences between the groups of students using the systems as part of their classroom instruction and the groups of students in standard classrooms. Similarly, the report of the National Mathematics Advisory Panel (2008) points to mixed results in the research on computer-based tutorials.

It could be argued, however, that an ITS should yield higher learning gains than traditional systems with computer-based training, multimedia, hypertext and hypermedia (Corbett, 2001; Dodds & Fletcher, 2004; Graesser, Chipman, & King, 2008; Graesser, Conley, & Olney, in press; Wisher, & Fletcher, 2004). Dodds and Fletcher's (2004) meta-analysis could help to reconcile the results reported by Dynarski (2007) and those reported in the ITS literature.

Dodds & Fletcher (2004) reported effect sizes of 0.39 for computer-based training, 0.50 for multimedia, and 1.08 for intelligent tutoring systems. Dynarski et al. (2007) relied primarily on off the shelf products. While these products did include some intelligent tutoring systems such as Cognitive Tutor from Carnegie learning, the study primarily included Computer-based training (CBT) and multimedia systems with modest intelligence and adaptability to individual students.

There are several ITSs that target mathematics. Prominent examples include the Cognitive Tutors developed at Carnegie Mellon University for eighth grade algebra (Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger, Anderson, Hadley, & Mark, 1997; Ritter et al., 2007) and geometry (Alevan & Koedinger, 2001) and the ASSISTment system that has a similar model-tracing computational architecture for web applications (Koedinger, McLaughlin, & Heffernan, 2010; Mendicino, Razzaq, & Heffernan, 2009). This study implements the intelligent tutoring system called ALEKS (Assessment and LEarning in Knowledge Spaces) (Doignon & Falmagne, 1999). ALEKS was chosen because of previous experience with implementation not because it has been shown to be superior to other systems of its kind. In fact, recent research has shown that ALEKS and another major system Cognitive Tutor were both able to improve mathematics learning at equal levels (Sabo, Atkinson, Barrus, Joseph, & Perez, in press).

1.3. ALEKS, a mathematics based Intelligent Tutoring System

ALEKS is a Web-based learning system with artificial intelligence components (See Figure 1 for screenshot). Its artificial intelligence is based on a theoretical framework called Knowledge Space Theory (KST) (see <http://wundt.uni-graz.at/kst.php>). KST allows the representation in the computer's memory of an enormously large number of possible knowledge states that organize a scholarly subject. Rather than giving a score or series of scores that

describe a student's overall mastery of the subject, KST allows for a precise description of what the student knows, does not know, and is ready to learn next. According to KST, a subject such as arithmetic or Algebra I can be parsed into a set of problem types, with each problem type covering a specific concept (or skill, fact, problem-solving method, etc.). A student's competence can then be described by the set of problem types that the student is capable of solving. This set is called the student's *knowledge state*. A *knowledge space* is the collection of all of the knowledge states that might feasibly be observed in a population. Each mathematics subject matter typically has 250-350 problem types and several million knowledge states.

At the heart of ALEKS is the system's assessment engine. It attempts to uncover, by efficient questioning, the knowledge state of a particular student. The process usually takes from 25 to 35 questions that are given as a diagnostic test when the student starts using the system. This efficiency stems from the many inferences made by the system via the knowledge space.

At the beginning of a KST assessment, each knowledge state is given some initial probability. A question (problem type) is selected and based on the student's answer, the probabilities are updated. If the student answers correctly, then each knowledge state containing that problem type is increased in probability. If the student answers incorrectly, then each of those states is decreased in probability. The next question is selected according to an algorithm that is as informative as possible according to a particular measure. The process continues within a decision cycle until there is one knowledge state with a much higher probability than the others and this is the problem type assigned to the student.

ALEKS then provides, in the form of a pie chart and report, a summary of what the student knows, does not know, and is ready to learn. The learner can then choose from among the problem types ready to be learned. Once the system determines that the problem type had

been mastered, it is added to the student's knowledge state, and another problem type that is ready to be learned can be chosen. Subsequent assessments update the student's knowledge state.

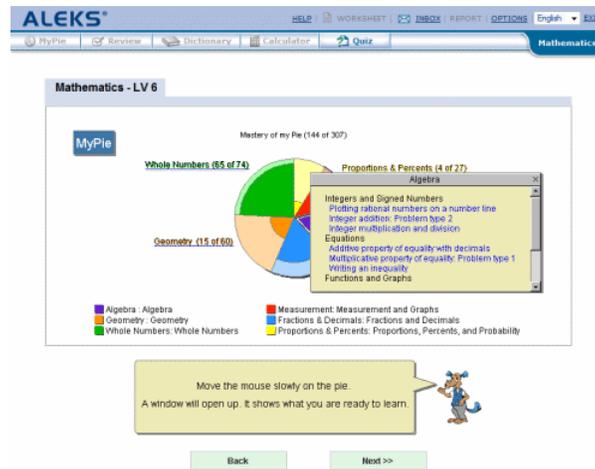


Figure 1. Screenshot of the ALEKS problem selection interface

The ALEKS system has some similarities to traditional computer based training (CBT) systems. It implements mastery learning where the learner (a) studies material presented in a lesson, (b) gets tested with a multiple choice test or another objective test, (c) gets feedback on the test performance, (d) restudies the material if the performance in (c) is below threshold, and (e) progresses to a new topic if performance exceeds threshold. The order of topics presented and tested follows a prerequisite structure where some skills need to be mastered before progress can be made on other skills. However, ALEKS moves beyond CBT by using Bayesian networks to adaptively select the next skill for a student to work on. The Bayesian networks of the knowledge space model attempts to fill learning deficits and correct misconceptions adaptively and dynamically (Doignon & Falgagne, 1999). It tracks the knowledge states of learners in fine detail and adaptively responds with assignments that are sensitive to these knowledge states.

1.4. ALEKS and the Tennessee Comprehensive Assessment Program

Sullins and colleagues (Sullins, Meister, Craig, Wilson, Bargagliotti, and Hu, in press) reported a strong relationship between ALEKS performance and Tennessee state test scores from

the TCAP (Tennessee Comprehensive Assessment Program). Two separate studies investigated the relationship between students' interaction with ALEKS and mathematics achievement test scores. Study 1 included sixth, seventh and eighth graders enrolled in two mid-south urban school systems for a total of 218 students. Students participated in their normal curriculum as determined by their respective school and school system. In addition, they were given access to the ALEKS system. Results of a correlation analysis showed strong and statistically significant correlation ($r = .84, p < .01, n = 216$) between the TCAP scores and assessment performance in ALEKS. This result substantiates the claim that the ALEKS measurements are closely aligned with TCAP, the state standard for mathematics.

Study 2 was designed in order to partially replicate the results found in Study 1, but this time using a different school district and sample. Teachers used ALEKS as part of their regular mathematics instruction. Teachers allocated one day (usually Friday) each week as an "ALEKS day". Study 2 included 124 fifth graders, 98 sixth graders, and 99 seventh graders for a total sample of 321 students. Due to the lack of availability of TCAP scores, the final sample did not contain any individuals in grade eight. Results of the correlational analysis revealed a statistically significant positive correlation between performance in ALEKS and TCAP scores when all of the grades were combined ($r = .74, p < .0001, n = 321$). Once again, the ALEKS measures are aligned with the state standards.

1.5. A randomized study of an after-school program with ALEKS

Afterschool time offer a significant opportunity to improve student learning and abilities especially when students can interact with experts (Koch, Georges, Gorges, & Fujii, 2010). However, access to these experts, especially expert tutors, is expensive. Learning technology might be able to fill in the gap, but only if it is as effective as the alternative.

This study reports Year Two results of a three-year afterschool mathematics program that aims to help students in 6th grade from a west Tennessee school district improve student achievement in mathematics. A *Randomized Alternative-Treatment Design with Pretest* compared the ALEKS intelligent tutoring system to a condition with human tutors. This paper addresses two major research questions: (1) How does computer mediated learning from ALEKS compare to learning from a teacher in an after-school setting when assessing student achievement on the Tennessee Comprehensive Assessment Program (TCAP)? (2) How do students in classrooms with computer mediated learning from ALEKS compare to students in teacher-led classrooms on classroom management issues of student's behavior (i.e. conduct, student involvement) and can this individualized learning provided by the system impact the direct participation needed from the teacher to meet student requests for assistance?

2. Methods

2.1. Participants

The 253 sixth grade participants were recruited for the after-school program from four intermediate schools in a school district in west Tennessee. The district serves both a mid-sized city and the surrounding rural county with 13,607 students in grades Pre-K–12, distributed among 28 schools. The school system has a largely economically disadvantaged population (68.2%) and large minority student enrollment (56.3% African American, 3.4% Hispanic, 39.3% White, and 1% other). The 6th grade students were recruited at school assemblies, by fliers sent home to parents, and at school functions open to the parents and family of students at the school.

At ten random dates, all students in attendance were provided a small gift. All daily gifts were purchased from Oriental Trading Company (<http://www.orientaltrading.com/>). At the end of the program, students who achieved very high attendance were entered into drawings for

either a laptop (>90% attendance), one of two iPod shuffles and one of two \$25 gift cards (>80% attendance). One set of these items was provided to students at each school.

2.2. Materials and assessment.

2.2.1. Instructional content.

In both the ALEKS and teacher led conditions, the mathematics taught was guided by the Tennessee state performance indicators (SPIs). SPIs are topics that each student is expected to have mastered by the end of the school year based on grade-level (See Appendix A). In ALEKS, the method of incorporating the SPIs is as simple as selecting the topics in the program. In the teacher led condition, daily lesson plans were created to align with the SPIs by a mathematics education expert and an expert teacher, who were both members of the research team (See Appendix B for example lesson plan). In the teacher led condition, unlike the ALEKS led condition that uses the individualized learning plans, if a student missed a day they would not receive instruction on that topic.

2.2.2. Assessments.

For both the ALEKS and teacher led conditions the outcome measure of performance was the TCAP reported as a normal curve equivalent (NCE) score. This assessment is given at the end of each year for grades 3-8 to all students in Tennessee. It is the test used to evaluate the level at which each student has mastered the SPIs for that year. The scores of the 5th grade TCAP were used to assess students' pre-program mathematics knowledge whereas the scores of the 6th grade TCAP were used as the posttest. The TCAP NCE score is out of 100 and is normalized based on the students score compare to equivalent students within the state. So, the score can be view as how well student performed relative to the rest of the state with 50 equal to the state average.

2.2.3. Teacher ratings.

Each day of the program, classroom teachers gave ratings of student's conduct (How was student name (ID number)'s conduct today?), task involvement (How involved was student name (ID number) in today's class?), and need for additional assistance (Did student name (ID number) require any assistance in class today?). Conduct was rated on a 3-point scale of from 0-2 with 0 points for poor conduct, 1 point for good conduct and 2 points for Excellent conduct. Task involvement was also rated on a three point scale from 0-2 with 0 for not involved, 1 for somewhat involved and 2 for actively involved. The assistance score was rated as 0 if no help was received and 1 if additional help with Mathematics beyond that of the standard class was provided.

2.3. Procedures

2.3.1. Teacher and Facilitator Training.

Teachers, previously certified to teach 6th grade mathematics by the state, were recruited to conduct the after-school program. They were paid at a rate of \$20 per hour. Teachers were randomized into either treatment or control classrooms. Training on the procedures for both conditions was given to the teachers as a group prior to the program beginning. This was a one-time session that lasted 3 hours. During this training, teachers were provided an overview of the program, training on how to use the ALEKS system and the lesson plans, a description of how ALEKS and the lesson plans were linked to state performance indicators, and the time schedule of the program. Teachers did not know their assigned role until after the training.

Each school also had an onsite facilitator that was appointed by the school's Principal. Facilitators performed three functions. They provided oversight of the program at the local school level (e.g. enforcement of schedules, placement of students into correct classrooms, and

overseeing snack breaks) and more assistance to the teachers in dealing with student issues (e.g. discipline issues and removal of students from the program). Facilitators also handled any distribution of materials such as fliers during the school day. They were paid at a rate of \$25 per hour for the hours of the after school program, but not for work during the school day.

2.3.2. Implementation.

The after-school program was divided into two conditions: The ALEKS condition (treatment) and the teacher led condition (control). At each school, there were four classes: two ALEKS and two control with one teacher in charge of each class. Class size was capped at 20, which accommodated room for 80 students at each school.

In the ALEKS condition, students were tutored using the ALEKS program while in the teacher led condition students were taught as a class by the teachers. In the ALEKS condition, teachers took on the role of supervisor providing help with technical issues with the computer and mathematics help only by request by the student.

The program was held after school for two hours twice a week. The two hour periods included three 20 min tutoring sessions divided by two 20 min breaks with 10 min at the beginning and end for set-up and dismissal. During the first 20 min break, students were provided with district-approved snacks and in the second break student were allowed to play games. During the 20 min tutoring sessions, students in the ALEKS condition interacted with the ALEKS system during all three sessions. In the teacher led condition, students were taught using the *I do-We do-You do* technique. This technique has three sessions. In the first session, the teacher modeled math problems and worked through them. In the second, the class worked on transfer activities as a group. Students worked through new problems independently in the third session. Every

fifth day, a short assessment on recent material was given in both conditions to evaluate progress.

2.4. Data Analysis

Data were collected from the district and from the ALEKS program. The district provided background characteristics (gender and racial/ethnic background) of each student as well as student TCAP scores from both 5th grade (before the program, TCAP 2010) and 6th grade (after the program, TCAP 2011). The ALEKS program collected information as to how often students attended. Each teacher in the Teacher led condition and each monitor in the ALEKS condition kept student attendance throughout the duration of the program.

For both the ALEKS and Teacher led conditions, the outcome measure of performance was the TCAP NCE score in mathematics. The scores of the 5th grade TCAP were used to assess students' pre-program mathematics knowledge whereas the scores of the 6th grade TCAP were used as the posttest.

3. Results

3.1. Between group differences

Because there were only two conditions in the study, a t-test was conducted on student's 5th grade TCAP performance (student performance prior to entering the program). This did not indicate any significant differences between conditions, with mean scores of 46.19 and 43.98 in the ALEKS and Teacher led conditions, respectively, $t(251) = -0.971$, $p = .33$, $d = 0.12$. A t-test conducted on students' 6th grade TCAP performance (student performance after completion of the program) comparing the ALEKS versus Teacher led conditions also showed no significant differences between the groups, with corresponding means of 42.16 and 39.05, $t(251) = -1.40$, p

= .16, $d = 0.18$. Although scores were favoring the ALEKS condition, they were not significant statistically.

A series of t-tests were conducted on the teacher’s daily ratings of student’s task involvement level (0-2 teacher rating on student’s involvement in their task), class conduct (0-2 teacher rating on students classroom conduct), and assistance required (proportion of time student requested help from the teacher) during the after school program. Significant differences were not observed for the involvement, $t(251) = -0.69, p = .49, d = 0.05$, or conduct, $t(251) = 0.16, p = .87, d = 0.02$, variables. However, there was a large difference observed for the amount of additional assistance provided to students, $t(251) = 23.32, p < .001, d = 2.91$ with students in the ALEKS condition requiring less assistance from teachers. The means and standard deviations are provided in Table 1.

Table 1.

Means and standard deviations by condition for 5th grade and 6th grade TCAP student involvement, conduct, and assistance needed.

	ALEKS		Teacher	
	M	SD	M	SD
5 th grade TCAP	46.19	19.16	43.98	17.14
6 th grade TCAP	42.16	18.33	39.05	17.18
Involvement	1.77	.36	1.75	.37
Conduct	1.62	.44	1.63	.42
Assistance	.05	.11	.65	.27

3.2. Regression analysis for program effectiveness

A multiple regressions analysis was conducted on the student's 6th grade TCAP data to determine the amount of the variability predicted by specific student and program elements. This analysis predicted 59% of the observed variance for students' 6th grade TCAP NCE scores. The results revealed higher TCAP NCE scores on 6th grade were predicted by 5th grade TCAP NCE scores, and higher attendance, whereas gender, race, and experimental treatment were not significant. The regression results are presented in Table 2.

Table 2.

Multiple Regression Analysis on 6th grade TCAP scores for students in the after-school program

Predictor Variable	Unstandardized Coefficients	SE	M	SD
5 th grade TCAP score	0.74**	0.04	45.06	18.16
ALEKS treatment	1.23	1.45	1.49	0.50
Gender	0.90	1.47	1.56	0.50
Ethnicity	-0.38	1.35	1.85	0.538
Attendance	0.10*	0.05	26.94	15.58
Constant	2.31	4.65		

N = 253

R-squared = 0.593

** p<0.001, * p<0.05

4. Discussion

We found that students in the ALEKS condition are equal or higher (although not statistically significant) than the teacher led condition on TCAP scores. This is encouraging

because the curriculum for the after-school program in the teacher condition was created by mathematics education experts and implemented by certified and highly experienced teachers using classroom-based technologies such as smart boards. As such, the quality of the lesson plans was very high. In addition, due to attrition, some of the teachers led classrooms had a very small student-teacher ratio leading to optimal teaching conditions (Finn et al., 2003).

Nevertheless, the ALEKS condition had an effect size advantage of 0.18 over the Teacher condition. While this was not statistically significant, it was encouraging and consistent with the evaluation of the first year of the program (Hu et al., 2012).

The teacher ratings are also supportive of the overall effectiveness of the program. Ratings for student conduct and student involvement indicate that students were highly engaged and participating in both classroom types. This is consistent with Beck's finding that student conduct and involvement tend to be good in afterschool settings (1999). As stated earlier, the program had a small class size. This has been shown in previous research to be a strong factor of the good conduct and involvement of students (Finn et al, 1996; Finn et al, 2003). The small class size in both the teacher-led and the ALEKS-led program allowed for teachers to devote more time to individual students and could have helped to keep the students' engaged. The ALEKS system provides an individualized learning sequence to students providing problems the students are ready to learn. This constant challenge could have also increased student's involvement in the assigned task without direct teacher involvement.

However, the decreased amount of assistance needed by students in the ALEKS condition could point to an added value for the use of the technology enhanced program in after school settings. The decreased assistance required could have been caused by two factors related to the system. First, as discussed above, the ALEKS system used Knowledge Space Theory to

suggest problems that students were ready to learn. This should have cut down on the help needed. Second, the system provides generic worked examples of how to solve each type of problem. This type of just-in-time help has been shown to be effective for facilitating robust learning and transfer of mathematical concepts (Alevan, 2013). However, it is also known that this type of help often breaks down within an intelligent tutoring system (Alevan, Stahl, Schworm, Fischer, & Wallace, 2003) and this is especially true for low domain students (Wood & Wood, 1999). So, students can use help to acquire problem solving steps and not deeper understanding. Thus, learners apply help behavior referred to *gaming the system* (Baker, Walonoski, Hefernan, Roll, Corbett, & Koedinger, 2008) to move forward by taking the answers to the next steps of the problem directly from the system help. Other times, students use maladaptive strategies because they lack the basic knowledge to benefit from the help (Alevan, 2013). While it is possible that both of these methods took place within the system, the help system within ALEKS provides a worked example of problem solving (Atkinson, Derry, Renkl, & Wortham, 2000) for the problem skill. Observing these worked examples could provide information to conceptually understand the problem while they are being solved (Craig, Chi, & Vanlehn, 2009) within ALEKS, but it does not provide the step by step information needed to solve the problem. This prevents gaming the system behavior using the help system. It would appear that the conceptual worked example help allows students to move forward within ALEKS with only rarely relying on teachers for problem specific help.

While it is most likely a combination of both of these factors that is decreasing the need for assistance from teachers, future research is needed to determine the impact of these potential factors on the observed effect. However, it should be noted that the amount of assistance needed was not significantly correlated to students' TCAP NCE scores and the relationship was weak (r

= -.16). While it is not surprising that the relationship is negative, that the relationship remained small and non-significant indicated that students were able to get the assistance they needed from the system.

This would allow for two possible adaptations of the program. First, because additional assistance from the teacher was not required, schools could use this type of program if certified mathematics teachers were not available. Both conditions of the current program only allowed the teacher to assist students if help was requested and could not move forward without it. Second, the program could be structured to encourage teachers to assist students. The blending of assistance from the teacher and ALEKS could improve the students overall improvement in the after-school program. However, further research would be required to determine the effectiveness of these modifications.

Overall, the second year of the program was successful. While statistical differences between conditions were not observed, the overall improvement on TCAP NCE scores of students in the program indicates that the program could have two equally effective programs. This opens the door for school systems to choose a program based on their individual needs and resources. For school systems that have limited availability of certified teachers, a technology option for an after-school setting would be available which would resulting in no penalty in overall student learning from the after-school experience.

5. Acknowledgements

6. References

- Achilles, C. M. (1999). Let's put kids first, finally: Getting class size right. Thousand Oaks, CA: Corwin Press.
- Aleven, V. (2013). Help Seeking and Intelligent Tutoring Systems: Theoretical Perspectives and a Step Towards Theoretical Integration. In R. Azevedo & V. Aleven (Eds.), *International Handbook of Metacognition and Learning Technologies* (pp. 311-335). Springer New York.
- Aleven, V., & Koedinger, K. R. (2001). Investigations into Help Seeking and Learning with a Cognitive Tutor. In R. Luckin (Ed.), *Papers of the AIED-2001 Workshop on Help Provision and Help Seeking in Interactive Learning Environments*. pp. 47-58. Retrieved from <http://www.hcrc.ed.ac.uk/aied2001/workshops.html>
- Aleven, V., Stahl, E., Schworm, S., Fischer, F., & Wallace, R. (2003). Help seeking and help design in interactive learning environments. *Review of Educational Research, 73*(3), 277-320.
- Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *The Journal of the Learning Sciences, 4*, 167-207.
- Atkinson, K., Derry, S. J., Renkl, A., & Wortham, D. (2000). Learning from examples: Instructional principles from the worked examples research. *Review of Educational Research, 70*, 181-214.
- Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., Koedinger, K. (2008) Why Students Engage in "Gaming the System" Behavior in Interactive Learning Environments. *Journal of Interactive Learning Research, 19* (2), 185-224.
- Beck, E. (1999). Prevention and intervention Programming: Lessons from an after-school program, *The Urban Review, 31*, 107-124.

- Bourke, S. (1986). How smaller is better: Some relationships between class size, teaching practices, and student achievement. *American Educational Research Journal*, 23, 558–571.
- Corbett, A. T. (2001). Cognitive computer tutors: Solving the two-sigma problem. *User Modeling: Proceedings of the Eighth International Conference*, 137-147.
- Craig, S. D., Chi, M. T. H., & VanLehn, K. (2009). Improving classroom learning by collaboratively observing human tutoring videos while problem solving. *Journal of Educational Psychology*, 101, 779–789.
- Cross, A. B., Gottfredson, D. C., Wilson, D. M., Rorie, M., & Connell, N. (2009). The impact of after-school programs on the routine activities of middle-school students: Results from a randomized, controlled trial. *Criminology & Public Policy*, 8, 391-412.
- Dearing, E., Wimer, C., Simpkins, S. D., Lund, T., Bouffard, S. M., Caronongan, P., Kreider, H. & Weiss, H. (2009). Do neighborhood and home contexts help explain why low-income children miss opportunities to participate in activities outside of school?. *Developmental Psychology*, 45, 1545-1562.
- Dodds, P., & Fletcher, J. D. (2004). Opportunities for new smart learning environments enabled by next generation web capabilities. *Journal of Educational Multimedia and Hypermedia*, 13, 391-404.
- Doignon, J. P., & Falmagne, J. (1999). *Knowledge spaces*. Springer-Verlag, Berlin
- Dynarski, M., Agodini, R., Heaviside, S., Novak, T., Carey, N., Campuzano, L., et al. (2007). Effectiveness of reading and mathematics software products: Findings from the first student cohort. U.S. Department of Education, Institute of Education Sciences, Washington, DC.

- Fashola, O.S., (1998). *Review of extended day and after school program and their effectiveness.* (CRESPAR) Report No. 24). Retrieved from www.csos.jhu.edu/crespar/techreports/Report24.pdf
- Finn, J. D., Pannozzo, G. M. & Achilles, C. M. (2003). The “Why’s” of class size: Student behavior in small classes, *Review of Educational Research*, 73, 321-368.
- Finn, J. D., Fulton, D., Zaharias, J., & Nye, B. A. (1989). Carry-over effects of small classes. *Peabody Journal of Education*, 67, 75–84.
- Finn, J. D., Pannozzo, G. M., & Voelkl, K. E. (1995). Disruptive and inattentive-withdrawn behavior and achievement among fourth graders. *Elementary School Journal*, 95, 421–434.
- Gayle, C. (2004). *After school programs: Expanding access and ensuring quality.* Progressive Report. Retrieved from http://www.ppionline.org/documents/afterschool_0704.pdf
- Graesser, A. C., Conley, M. W., & Olney, A. M. (in press). Intelligent tutoring systems. In S. Graham, & K. Harris (Eds.), *APA handbook of educational psychology*. Washington, DC: American Psychological Association.
- Graesser, A. C., Chipman, P., & King, B. G. (2008). Computer-mediated technologies. In J. M. Spector, M. D. Merrill, van Merriënboer, J. J. G. & M. P. Driscoll (Eds.), *Handbook of research on educational communications and technology*, 3rd ed. (pp. 211-224). Taylor & Francis, London.
- Heffernan, N.T., Koedinger, K.R., & Razzaq, L. (2008). Expanding the model-tracing architecture: A 3rd generation intelligent tutor for Algebra symbolization. *International Journal of Artificial Intelligence in Education*, 18, 153-178.
- Hu, X., Craig, S. D., Bargagliotti A. E., Graesser, A. C., Okwumabua, T., Anderson, C., Cheney, K. R., & Sterbinsky, A. (2012). The effects of a traditional and technology-based after-

school program on 6th grade students' mathematics skills. *Journal of Computers in Mathematics and Science Teaching*, 31, 17-38.

Jackson, K. R. (2011). What factors contribute to a successful computer-based after-school program for at-risk children in an urban middle school? (Doctoral dissertation). Retrieved from <http://gradworks.umi.com/34/79/3479087.html>

Kanter, A. (2001). After-school programs for adolescents. *NASSP Bulletin*, 85(626), 12-21.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, 8, 30-43.

Koch, M., Georges, A., Gorges, T., & Fujii, R. (2010). Engaging youth with STEM professionals in afterschool programs. *Meridian*, 13, 1-18. Retrieved from <http://www.ncsu.edu/meridian/winter2010/koch/index.htm>

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, 8, 30-43.

Koedinger, K., McLaughlin, E. & Heffernan, N. (2010) A Quasi-Experimental Evaluation of an On-line Formative Assessment and Tutoring System. *Journal of Educational Computing Research*, 4, 489 – 510.

Kugler, M. R. (2001). After school programs are making a difference. *NASSP Bulletin*, 85(626), 3-11.

Lauer, P., Akiba, M., Wilkerson, S., Apthrop, H., Snow, D., & Martin-Glenn, M. (2006). Out-of-school time programs: A metanalysis of effects for at-risk students. *Review of Educational Research*. 76, 275-313.

- Mazzotti, V. L., Wood, C. L., Test, D. W., & Fowler, C. H. (2012). Effects of Computer-Assisted Instruction on Students' Knowledge of the Self-Determined Learning Model of Instruction and Disruptive Behavior. *The Journal of Special Education, 45*(4), 216-226.
- Mendicino, M., Razzaq, L. & Heffernan, N. T. (2009) Comparison of Traditional Homework with Computer Supported Homework. *Journal of Research on Technology in Education, 41*, 331-359.
- Miller, B. M. (2003). *Critical hours: After school programs and educational success*. Brookline, MA: Nellie Mae education Foundation. Retrieved from http://www.nmefdn.org/unimages/documents/Critical_Hours.pdf
- National Center for Education Statistics (2008). *National assessment of educational progress: The nation's report card*.
- National Center for Educational Statistics (2009). *Program for International Student Assessment (PISA) International Data Explorer*. Available at: <http://nces.ed.gov/surveys/pisa/idepisa/>
- National Mathematics Advisory Panel (2008). *Foundations for success: The final report of the national mathematics advisory panel*. Washington, DC: US Department of Education.
- Parette, H. P., Stoner, J. B., & Watts, E.H. (2009). Assistive technology user group perspectives of early childhood professionals. *Education and Training in Developmental Disabilities, 44*, 257-270.
- Pearson (2011). *MyMathLab* [software]. Available from <http://www.mymathlab.com/>
- Peterson, P. L., Swing, S. R., Stark, K. D., & Waas, G. A. (1984). Students, cognitions and time on task during mathematics instruction. *American Educational Research Journal, 21*, 487-515.

- Pierce, K. M., Bolt, D. M., Vandell, D. L. (2010). Specific features of after-school program quality: Associations with children's functioning in middle childhood. *American Journal of Community Psychology, 45*, 381-393.
- Righi, R. A. (2012). *The Impact of Laptop Computers on Student Learning Behaviors as Perceived by Classroom Teachers* (Doctoral dissertation, University of Toledo).
- Ritter, S., Anderson, J. R., Koedinger, K. R., Corbett, A. (2007) Cognitive Tutor: Applied research in mathematics education. *Psychonomic Bulletin & Review, 14*, 249-255.
- Sabo, K. E., Atkinson, R. K., Barrus, A., Joseph, S., & Perez, R. S. (in press). Searching for the two sigma advantage: Evaluating algebra intelligent tutors. *Computers in Human Behavior*.
- Schacter, J. (1999). The impact of educational technology on student achievement: What the most current research has to say (ERIC Document Reproduction Service No. ED 430 537). Milken Exchange on Educational Technology, Santa Monica, CA
- Seidman, A. (2005). The Learning Killer: Disruptive Student Behavior in the Classroom. *Reading improvement, 42(1)*, 40.
- Spivak, G., & Cianci, N. (1987). High-risk early behavior pattern and later delinquency. In J. D. Burchard & S. N. Burchard (Eds.), *Prevention of delinquent behavior* (pp. 44–74). Beverly Hills, CA: Sage.
- Swift, M. S., & Spivak, G. (1968). The assessment of achievement-related classroom behavior. *Journal of Special Education, 2*, 137–149.
- Sullins, J, Meister, R., Craig, S.D., Wilson, W. M., Bargagliotti, A., & Hu, X. (in press). Is there a relationship between interacting with a mathematical intelligent tutoring system and students performance on standardized high-stake tests? In D. Albert, C. Doble, D. Eppstein, J. Falmagne & X. Hu (Eds.), *Knowledge Spaces: Applications to Education*.

- Wisher, R. A., & Fletcher, J. D. (2004). The case for advanced distributed learning. *Information & Security: An International Journal*, 14, 1-25.
- Wood, H., & Wood, D. (1999). Help seeking, learning and contingent tutoring. *Computers and Education*, 33, 153–169.
- Vandell, D. L., Reisner, E., Brown, B., Dadisman, K., Pierce, K., Lee, D., & Pechman, E. (2005). *The study of promising afterschool: Examination of intermediate outcomes in year 2*. Madison, Wisconsin: Authors. Retrieved from http://www.wcer.wisc.edu/childcare/pdf/pp/year_2_report_final.doc
- Vandell, D. L., Reisner, E., & Pierce, K. (2007). *Outcomes linked to high-quality after school programs*. Washington, D.C: Policy Studies Associates Inc. Retrieved from <http://www.gse.uci.edu/childcare/des3.html>
- VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46, 197-221.

Appendix A

Session	Objective	Grade Level Expectation	SPI
1	TSW use area models to represent multiplication of fractions	GLE 0606.2.1 GLE 0606.1.4	SPI 0606.2.1
2	TSW create and solve contextual problems that lead naturally to division of fractions	GLE 0606.2.1 GLE 0606.1.2	SPI 0606.2.1
3	TSW solve problems involving the addition and subtraction of fractions and mixed numbers and will explain the procedure used	GLE 0606.2.1 GLE 0606.1.2	SPI 0606.2.2
4	TSW solve problems involving the multiplication and division of fractions and mixed numbers and will explain the procedure used	GLE 0606.2.1 GLE 0606.1.2	SPI 0606.2.2
5	TSW solve problems involving the addition and subtraction of decimals and will explain the procedure used	GLE 0606.2.1 GLE 0606.1.2	SPI 0606.2.4
6	TSW solve problems involving the multiplication and division of decimals and will explain the procedure used	GLE 0606.2.1 GLE 0606.1.2	SPI 0606.2.4
7	TSW convert between fractions and decimals	GLE 0606.2.4 GLE 0606.1.4	SPI 0606.2.5

8	TSW convert between fractions and decimals	GLE 0606.2.4 GLE 0606.1.4	SPI 0606.2.5
9	TSW convert between fractions and decimals	GLE 0606.2.4 GLE 0606.1.4	SPI 0606.2.5
10	TSW convert between fractions, decimals, and percents	GLE 0606.2.4 GLE 0606.1.4	SPI 0606.2.5
11	TSW solve problems involving ratios, rates, and %	GLE 0606.2.3 GLE 0606.1.4	SPI 0606.2.6
12	TSW solve problems involving ratios, rates, and %	GLE 0606.2.3 GLE 0606.1.4	SPI 0606.2.6
13	TSW use concrete, pictorial, and symbolic representation for integers	GLE 0606.1.4 GLE 0606.2.5	SPI 0606.1.3
14	TSW use concrete, pictorial, and symbolic representation for integers	GLE 0606.1.4 GLE 0606.2.5	SPI 0606.1.3
15	TSW solve one-step inequalities corresponding to given situations and represent the solution on a number line	GLE 0606.3.5 GLE 0606.1.4	SPI 0606.3.1
16	TSW use order of operations and parentheses to simplify expressions and solve problems	GLE 0606.3.3	SPI 0606.3.2
17	TSW model the commutative, associative, and distributive properties to show that two expressions are equivalent	GLE 0606.3.5 GLE 0606.1.4	SPI 0606.1.4

18	TSW use equations to describe simple relationships shown in a table or graph	GLE 0606.3.1 GLE 0606.1.5	SPI 0606.3.3
19	TSW write equations that correspond to given situations	GLE 0606.3.1	SPI 0606.3.5
20	TSW model algebraic expressions using algebra tiles	GLE 0606.1.8	SPI 0606.1.5
21	TSW rewrite expressions to represent quantities in different ways	GLE 0606.3.2	SPI 0606.3.4
22	TSW translate between verbal expressions/sentences and algebraic expressions or equations	GLE 0606.3.5	SPI 0606.3.5
23	TSW solve one-step linear equations using the algebra tiles	GLE 0606.1.8	SPI 0606.3.6
24	TSW solve two-step linear equations using the algebra tiles	GLE 0606.3.1 GLE 0606.1.8	SPI 0606.3.6
25	TSW solve two-step linear equations using number sense, properties, and inverse operations	GLE 0606.3.1	SPI 0606.3.6
26	TSW write and solve two-step linear equations corresponding to given situations	GLE 0606.3.1	SPI 0606.3.6
27	TSW use algebraic expressions and properties to analyze numeric and geometric patterns	GLE 0606.3.4	SPI 0606.3.7
28	TSW select the qualitative graph that models and	GLE 0606.3.5	SPI

	contextual situation; TSW write a contextual story modeled by a given graph		0606.3.8
29	TSW graph ordered pairs of integers in all four quadrants of the Cartesian coordinate system	GLE 0606.3.6	SPI 0606.3.9

30	TSW generate data and graph relationships between two quantities	GLE 0606.3.5	SPI 0606.3.9
31	TSW explore basic properties of triangles and quadrilaterals using a protractor and ruler	GLE 0606.4.1	SPI 0606.4.1
32	TSW classify triangles by side lengths and angle measure	GLE 0606.4.1	SPI 0606.4.1
33	TSW investigate the sum of the angles of a triangle and a quadrilateral using various methods	GLE 0606.4.1	SPI 0606.4.2
34	TSW find a missing angle measure in problems involving interior/exterior angles and/or their sums	GLE 0606.4.1	SPI 0606.4.2
35	TSW model and use the Triangle Inequality Theorem	GLE 0606.4.1	SPI 0606.4.3
36	TSW relate the area of a trapezoid to the area of a parallelogram and solve problems involving the area of trapezoids	GLE 0606.4.3	SPI 0606.4.1
37	TSW develop and use formulas to determine the circumference and area of circles	GLE 0606.4.3	SPI 0606.4.4
38	TSW solve contextual problems involving area and	GLE 0606.4.3	SPI

	circumference of circles		0606.4.4
39	TSW determine the surface area of prisms and cylinders	GLE 0606.4.4	SPI 0606.4.5
40	TSW determine the volume of prisms and cylinders	GLE 0606.4.4	SPI 0606.4.5
Extra Lesson 1	TSW determine the surface area of pyramids and cones	GLE 0606.4.4	SPI 0606.4.5
Extra Lesson 2	TSW determine the volume of pyramids and cones	GLE 0606.4.4	SPI 0606.4.5

Appendix B

J-MITSE Control

Lesson Plan

Session 25

Objective: TSW solve two-step linear equations using number sense, properties, and inverse operations.

Part I – Direct Instruction – 20 minutes

Introduction- connection between solving one-step linear equations and two-step linear equations.

A *two-step equation* is an equation with two operations. You can use *inverse operations* to solve equations that have more than one operation. What are inverse operations? (Ask the students to help you with the following: What is the inverse of addition? (subtraction). What is the inverse of subtraction? (addition). What is the inverse of multiplication? (division). What is the inverse of division? (multiplication). It is often a good plan to follow the order of operations in reverse when solving equations that have more than one operation.

Some common mistakes to watch for:

- *students want to multiply/divide BEFORE adding/subtracting when solving two-step equations.*
- *students subtract a number from both sides whenever they see a subtraction sign in the problem-remind them that the opposite of subtraction is ADDITION*

Teacher led classroom examples

Solve each two-step equation using division. After solving, check each answer.

Example 1: Solve and check $2x + 3 = 15$

Check answer: $2(6) + 3 = ?$ (It equals 15, so we are correct!!)

Example 2: Solve and check $-4w + 7 = -17$ Check answer: $-4(6) + 7 = ?$ (It equals -17)

Solve each two-step equation using multiplication. After solving, check each answer.

Example 3: Solve and check $5 + \frac{h}{2} = 13$ Check answer: $5 + (16/2) = ?$ (It equals 13)

Example 4: Solve and check $\frac{m}{5} - 8 = -14$ Check answer: $(-30/5) - 8 = ?$ (It equals -14)

As you go through the step of checking the solutions, students see the significance of the order of operations in solving equations.

Part II – Activity – 20 minutes

I have, Who has? Materials needed: index cards

Place each individual line on an index cards. When students receive their index card (Give out every card so that the activity will “work”. This means that some students may have two cards OR students may have to work in pairs where each pair has a card.) The teacher will keep the START card. Before beginning the activity, have students work out the equation on the card under WHO HAS? This will allow them to have an answer ready when their card is called and help the activity go more smoothly.) If someone breaks the “chain”, have each person solve their equation under WHO HAS? again to make certain they have the correct answer. If they have solved their equations properly, then they should go in the order below. The equations with fractions (where multiplication is required to solve) have the fractions given in parentheses.

Once everyone has their equation under WHO HAS? solved, begin the activity by reading the Start card.

I HAVE WHO HAS?

Start

$$5 \quad 2x + 3 = 7$$

$$-9 \quad 2x + 3 = 23$$

$$-112 \quad -7 + (r/3) = 3$$

$$2 \quad -6x - 1 = 5$$

$$10 \quad 8 + (a/4) = 2$$

$$30 \quad -4w - 2 = 6$$

$$-1 \quad (x/6) + 2 = 4$$

$$-24 \quad (u/3) + 6 = 18$$

$$-2 \quad (k/2) + 12 = 2$$

$$12 \quad 4m - 8 = -24$$

$$36 \quad -11 - 3m = -20$$

$$-20 \quad 9x - 4 = 41$$

$$-4 \quad (r/9) - 5 = 1$$

$$3 \quad 5x + 6 = 41$$

$$54 \quad -3p - 8 = 19$$

$$7 \quad (m/-7) - 14 = 2$$

Part III – Application/Assessment – 20 minutes

In the last 20 minutes, students should work individually on the following problems solving two-step equations. Use this time to monitor the progress of individual students.

Solve the following equations. Make sure to check each answer.

1. $2x + 3 = 5$ (answer: 1)
2. $5x - 2 = -7$ (answer: -1)
3. $M/2 + 32 = 40$ (answer: 16)
4. $13 + y/-7 = 12$ (answer: 7)
5. $2x - 5 = -5$ (answer: 0)
6. $-3c + 14 = 8$ (answer: 2)
7. $(g/4) - 11 = 1$ (answer: 48)

If time permits, have students go to the board to share solutions and answers with the class.