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Assessing the effectiveness of an artificial intelligence tutoring system for improving college-level mathematics preparedness in high school students

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Abstract

Intelligent Tutoring Systems (ITS) have been used to help high school students transition from the mathematics taught in high school to the mathematics expected at colleges and universities. The purpose of this study was to examine relationships between high school students' performance in Assessment and LEarning in Knowledge Spaces (ALEKS) Placement, Preparation, and Learning (PPL) Modules and performance on the ALEKS College Mathematics Placement Exam. The participants in this study were 100 students from five high schools in the United States. Each student was placed into one of two groups: the ALEKS Group, who completed the ALEKS Pre-Calculus Learning Modules, and the Non-ALEKS Group, who did not complete the modules. Students' scores were compared statistically to test for significant differences. The analysis included a 2x2 mixed ANOVA to measure how assignment of the modules affected exam scores. A logistic regression was used to assess differences between the two groups in placing into college algebra. A statistically significant difference was found in exam scores between the ALEKS Group and the Non-ALEKS Group which indicated that assignment to the ALEKS PPL Pre-Calculus Learning Modules did increase performance on the ALEKS College Mathematics Placement Exam. Conversely, assignment to the ALEKS PPL Pre-Calculus Modules did not increase students' likelihood of placing into College Algebra. The amount of time students spent taking the exam influenced student outcomes on the ALEKS Mathematics Placement exam. These results show that schools could implement Intelligent Tutoring Systems into their current mathematics classrooms to help students increase their scores on college entry mathematics placement exams.

Keywords: intelligent tutoring systems, artificial intelligence, quantitative literacy education, college mathematics preparation

Introduction

The purpose of this study was to examine the impact of Intelligent Tutoring Systems (ITS) on relationships between high school students' performance in Assessment and LEarning in Knowledge Spaces (ALEKS) Placement, Preparation, and Learning (PPL) Modules and performance on the ALEKS College Mathematics Placement Exam. Intelligent Tutoring Systems are computer-based educational tools that utilize concepts from various disciplines such as Artificial Intelligence (AI), cognitive science, education, computational linguistics, and mathematics (Graesser, Conley, & Olney, 2012). Because of the misalignment between the mathematics preparation students receive in high school and their readiness for college level mathematics (Conley, 2003), Intelligent Tutoring Systems, such as the ALEKS PPL program, have been created and are used ubiquitously in the secondary school setting (Oxman & Wong, 2014).

Various grants provided to many universities funded initial efforts to design ITS to mimic one-on-one tutoring for public K-12 schools (Oxman & Wong, 2014). Each learner's psychological state is modeled by the ITS to provide individualized instruction and adaptive remediation (Ma, Adesope, Nesbit, & Liu, 2014). The development of the ALEKS PPL intelligent tutoring program was the result of such grants. ITS has the potential to play an important role in addressing the problem of the misalignment between high school mathematics and college-level mathematics for many students.

Research Questions

Two main research questions about ITS effectiveness and utility guided this study:

1. *How does use of Intelligent Tutoring Systems (for this study, the ALEKS ITS) modules affect positive student performance over time on the college mathematics placement exam?*

2. *What is the difference between the non-ITS and the IST groups as the percentage of students who score high enough to place into College Algebra on the college mathematics placement exam?*

Literature Review

This study examined the ALEKS PPL as a supplement to regular instruction in senior-level high school mathematics classrooms as a potential way to reduce some of the misalignment between high school and college-level mathematics. ALEKS PPL is an Intelligent Tutoring System that individualizes learning by assessing each student's knowledge state and creating a personalized course of study based on each student's performance with previous concepts (ALEKS, 2018b). ALEKS is the first ITS to incorporate Knowledge Space Theory for assessment and teaching and determines what each student knows, and it offers material that the student is ready to learn (Advanced Customer Solutions, ALEKS Corporation, 2017). ITS programs, like ALEKS PPL, have great potential to supplement mathematics learning in K-12 classrooms by increasing students' mathematics knowledge through individualized learning. These individual mathematics experiences, with targeted mathematics practice, can impact a student's placement in college mathematics courses.

The field of ITS began with the publication of the book "Intelligent Tutoring Systems" by Sleeman and Brown in 1982. This book brought together researchers from various disciplines such as AI, cognitive science, and education, with the shared goal of improving learning through the use of adaptive and intelligent systems. Some ITS aimed to mimic the behavior of human tutors, while others adopted more idealized models. By the early 1990s, there were two major conferences dedicated to the development and testing of ITS: Intelligent Tutoring Systems and Artificial Intelligence in Education. The book "Building Intelligent Interactive Tutors" by Woolf, published in 2009, provides a detailed overview of ITS architectures and important contributions to the field over its 30-year history (Graesser, Conley, & Olney, 2012).

Commercial product developers have devoted a great deal of time to developing ITS that can offer remediation for those wanting to learn/relearn mathematics concepts. ITS are computer programs that are often self-paced, learner-led, and very adaptable. Their adaptability comes from being able to adjust to fit the specific needs and characteristics of the learner by providing individualized instruction (Ma et al., 2014; Steenbergen-Hu & Cooper, 2013). Although there is no replacement for a teacher in the classroom, and simply incorporating technology into the classroom does not increase performance significantly, there are ways that ITS can improve student readiness for college mathematics (Craig et al., 2013; Fine et al., 2009;

Sabo et al., 2013; Haulk et al., 2015). Therefore, looking at different ways that ITS can increase college readiness should be explored.

Research has shown that technology can have a positive impact on student learning in mathematics (Craig et al., 2013). Several studies have shown the effectiveness of using ITS in mathematics classrooms to improve student readiness for college mathematics (Craig, et al., 2013; Fine et al., 2009; Haulk, Powers, & Segalla, 2015; Sabo, Atkinson, Barrus, Joseph, & Perez, 2013). There is a need for this type of research because of the lack of studies that compare the use of an ITS to comparable classrooms that do not use an ITS for a full academic year.

The use of ITS, like the ALEKS PPL program, is only effective when used with fidelity because many factors may influence their effectiveness. Student attitudes, teacher support, and time spent with technology, all can play a role in student outcomes but unfortunately, there is limited research in this area. Using the technology for the recommended time given by the program designer should be used in the implementation of the program. Cheung and Slavin (2013) found that educational technology programs were more effective if they required more than 30 minutes per week than those that were used less.

Technology that is designed specifically to teach mathematics fits under both a tool for practicing skills and a tool for concept development. Tools for concept development are more focused on fostering the development of student sense making and understanding and attention to epistemology is often increased (Hoyles, Noss, & Kent, 2004).

Conceptual understanding is defined as the connections or relationships between ideas, and technology provides a medium for displaying and observing these relationships (Heid & Blume, 2008). With tools for practicing skills, tools are designed to efficiently organize student practice, provide students with rapid feedback, and can help students find the tutorial resources focused on the problem at hand (Drijvers et al., 2018; Roschelle et al., 2017). Intelligent tutoring systems, such as ALEKS PPL, fit into this category.

Methodology

This study used a quasi-experimental design to determine how the use of ALEKS (PPL) Modules by high school students relates to the students' performance on the ALEKS PPL Mathematics Placement Exam. ALEKS PPL is an artificially intelligent web-based learning and assessment system. The set of data that was used for this study was collected by the researchers during one full academic year under an approved IRB Protocol (#9350).

The existing data set consisted of two groups: The ALEKS PPL Group and the Non-ALEKS PPL Group. Classes in the ALEKS PPL Group participated in regular mathematics class sessions supplemented with ALEKS PPL Modules. Classes in the Non-ALEKS PPL Group participated in regular mathematics class sessions and did not use ALEKS PPL Modules. Both groups completed the ALEKS PPL Mathematics Placement Exam at the beginning and end of the academic school year.

Table 1 shows the number of participants with each teacher and participating school. The participants were 100 high school students, ages 16-18 who were enrolled in nine different class sections of College Prep Mathematics during their senior year of high school. The ALEKS PPL Group had 73 participants from three different high schools and the Non-ALEKS PPL Group had 27 participants from two different high schools.

Table 1: Numbers of Schools, Classes, Teachers, and Participants in the Study

Location	Number of classes	Number of teachers	ALEKS PPL group	No. of participants in each class	Total no. of participants
High School A	3	2	Yes	4, 22, 8	34
High School B	1	1	Yes	10	10
High School C	1	1	No	7	7
High School D	2	1	Yes	21, 8	29
High School E	2	1	No	8, 12	20
TOTALS	9	6			100

The quantitative data sources and measurements that were used for this study included: ALEKS PPL Mathematics Placement Exam Scores from October and May, ALEKS PPL Pre-Calculus Learning Module Mastery Scores for the ALEKS PPL Group, and ALEKS PPL Time Data. The data is analyzed using a 2x2 mixed Analysis of Variance (ANOVA), and logistic regression, along with descriptive statistics.

The first measure of student performance was scores on the ALEKS PPL Mathematics Placement Exam. The purpose of the ALEKS PPL Mathematics Placement Exam is to gather information about the current knowledge state of the student and to create an instructional plan that can teach students topics that they are most ready to learn (McGraw-Hill Education, 2020a; Yilmaz, 2017). The exam covers 314 interrelated mathematics topics by asking 30 questions and takes about one hour for students to complete.

The second measure was time data. This is the amount of time students spent taking each ALEKS PPL Placement Exam (called "exam time"). The "exam time" data was the amount of time students spent taking the exam. This time data allows the researchers to examine if the amount of time the student spent taking the exam is related to their exam scores.

Table 2: Description of Research Question, Measures, and Data Analyses Conducted in the Study

Research question	Measures	Data analyses
1. How does use of Intelligent Tutoring Systems (for this study, the ALEKS ITS) modules affect positive student performance over time on the college mathematics placement exam?	ALEKS Mathematics Placement Exam *scores in October and May*	**2X2 Mixed ANOVA** **DV** = *exam scores (continuous, both October and May)* **IVbs** = *group (0 = control, 1 = treatment)* **IVws** = *date (1 = October, 2 = May)*
2. What is the difference between the non-ITS and the IST groups as the percentage of students who score high enough to place into College Algebra on the college mathematics placement exam?	ALEKS Mathematics Placement Exam *scores in October and May; Log data on May exam time*	**Logistic Regression** **DV** = *post exam score (in May only) higher than cut off* **score** *(binary, 0=no, 1=yes)* **IV** = *group (binary, 0 = control, 1 = treatment)* **CV1** = *exam time taken (in May only, continuous minutes)* **CV2** = *exam score (continuous, in October only)*

ALEKS PPL Mathematics Placement Exam Growth Analysis

The first research question examined how students' assignment to the ALEKS PPL Pre-Calculus Learning Modules (group) affected growth over time (October vs. May) on the ALEKS PPL Mathematics Placement Exam. This question allows the researchers to investigate the effectiveness of assigning ITS in high school settings. The researchers used side-by-side boxplots of the exam scores between October and May for the two groups to show the between and within-group variation (Moore & McCabe, 2002).

The 2x2 mixed analysis of variance (ANOVA) is used to assess differences in ALEKS PPL Mathematics Placement Exam scores (dependent variable) by treatment group (independent variable – between-subject) at the two times (independent variable – within-subjects) to reveal any differences between the mean growth by assignment of ALEKS PPL (Moore & McCabe, 2002). The full sample of participants (N = 100) is utilized for this analysis to answer the first research question. The dependent variable was the ALEKS PPL Mathematics Placement Exam scores from October and May only. The independent variables were (1) the independent group (group), either the ALEKS PPL Group or the Non-ALEKS PPL Group, which is the between-subject variable; and (2) assessment date (date), taken in October or May, which is the within-subject or repeated measures variable.

Prior to the mixed ANOVA, we examined underlying assumptions. This included generating normal quantile plots for October and May exam scores and examining assumptions of normality. Homogeneity of variance was assessed via Levene's Test (Moore & McCabe, 2002). The test showed that the standard deviations were equal, and assumptions of normality were met. An omnibus F-test of the mixed ANOVA revealed that treatment assignment effected change in ALEKS PPL Mathematics Placement Exam scores over time (group x date interaction), so a post hoc Cohen's d effect size was computed on the May exam scores.

College Algebra Placement Analysis

Logistic regression was used in the analysis for the second research question to assess the difference between the Non-ALEKS PPL Group and the ALEKS Group in the probability that a student will score high enough to place into College Algebra (Score ≥ 46%). Within the full sample of participants (N = 100), the dependent variable was the ALEKS PPL Mathematics Placement Exam score from May dichotomized above or below the cut-off score to place into college algebra (0 = no, 1 = yes). The independent variable is the student group (ALEKS PPL or Non-ALEKS PPL).

Covariates included how much time students spent taking the May exam (minutes), as well as their initial placement exam score (from October). The metric that was used for exam scores was percent. This allowed for a good interpretation of the logistic regression odds ratio. This is because the interpretation of the odds ratio works by increasing the independent variable one unit, in this case, 1%, and then interpreting the odds ratio to describe the odds of the dependent variable occurring.

Results

The first research question examined whether assignment to the ALEKS PPL Pre-Calculus Learning Modules effected growth over time on the ALEKS Mathematics Placement Exam. The first part of the analysis to answer this research question included summary methods (e.g., box plots and descriptive statistics). In the second part of the analysis, we used a 2 x 2 mixed ANOVA. The figures and tables below show comparisons between the students who completed both the October exam and the May exam in the ALEKS Group (n = 73) and the Non-ALEKS Group (n = 27). Figure 1 shows side-by-side boxplots comparing the exam scores of the ALEKS Group with the Non-ALEKS Group. The median is shown by the horizontal line in the boxplot and the mean is shown by the x.

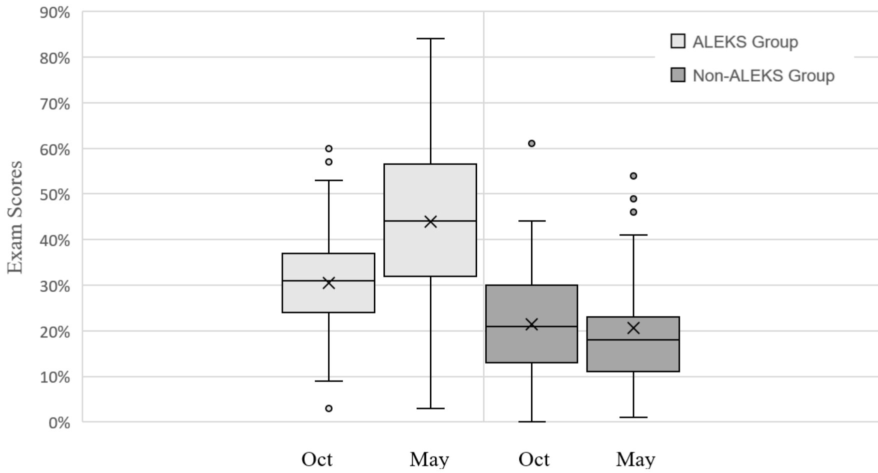

Figure 1. Boxplots of ALEKS Group vs Non-ALEKS Group for comparison of exam scores across time.

As Figure 1 shows, the ALEKS Group had a higher mean average on the October exam compared to the Non-ALEKS Group. This shows that the student exam scores were not equal between the groups at the beginning of the school year. The figure also shows that the ALEKS Group achieved greater gains in their exam scores from October to May compared to the Non-ALEKS Group. This suggests that working with the Pre-Calculus Learning Modules may have been effective in improving performance on the exam for the students who participated in this study.

Table 3: Descriptive Statistics of ALEKS Group and Non-ALEKS Group Exam Scores

Group	*n*	Min	Max	Mean	SD
ALEKS Group Oct Score	73	3	60	30.425	11.502
ALEKS Group May Score	73	3	84	43.973	17.007
Non ALEKS Group Oct Score	27	0	61	21.482	13.051
Non ALEKS Group May Score	27	1	54	20.556	14.001

As Table 3 shows, both groups had very similar minimum scores on the October and May exams and both groups had the same maximum score on the October exam. Additionally, there was a significant difference in the maximum score for May with the ALEKS Group having a high student score at 84% and the Non-ALEKS Group having a high student score at 54%.

The standard deviations for the October exams are relatively consistent among the groups and the same applies for the May exams. Most importantly, the mean scores for the ALEKS Group increased from 30.4% in October to 43.9% in May, while the mean score for the Non-ALEKS Group decreased from 21.5% in October to 20.6% in May. This shows that the ALEKS Group experienced greater overall gains in exam scores from October to May.

Figure 2 breaks down each group by teacher and uses boxplots to compare each group's exam scores from October and May. Every teacher in the ALEKS Group had students in their classes that averaged overall class gains on the exam from October to May.

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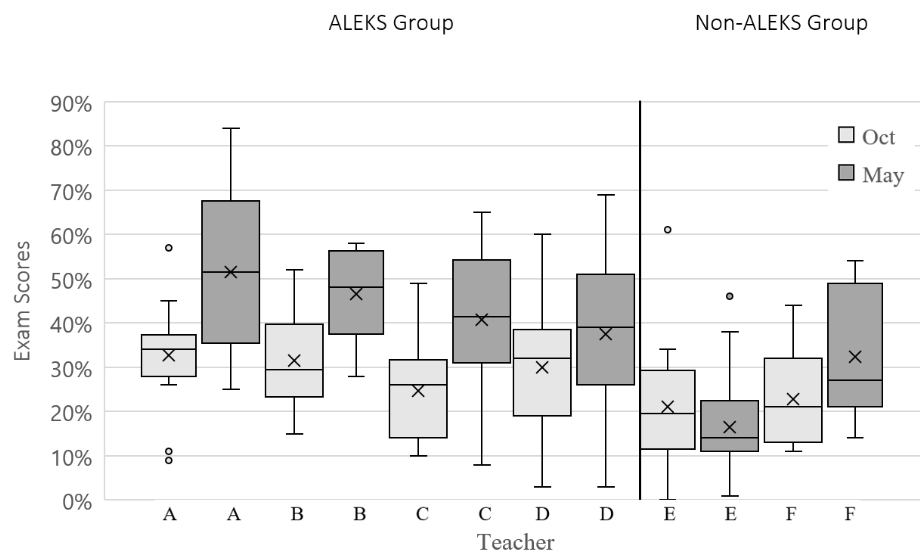

Figure 2. Boxplot of ALEKS and Non-ALEKS Group exam scores separated by group.

Conversely, Figure 2 shows the Non-ALEKS Group had one teacher (Teacher E) that had students in their class that averaged overall class losses on the exam, and one teacher (Teacher F) that had students in their class that averaged overall class gains on the exam.

Table 4: Descriptive Statistics of ALEKS Group and Non-ALEKS Group Exam Scores Separated by Teacher

Group	*n*	Min	Max	Mean	*SD*
ALEKS					
Teacher A Oct. Score	26	9	57	32.769	9.572
Teacher A May Score	26	25	84	51.539	17.326
Teacher B Oct. Score	8	15	52	31.500	11.551
Teacher B May Score	8	28	58	46.625	10.555
Teacher C Oct. Score	10	10	49	24.600	12.048
Teacher C May Score	10	8	65	40.800	16.645
Teacher D Oct. Score	29	3	60	30.035	12.676
Teacher D May Score	29	3	69	37.552	16.041
Non-ALEKS					
Teacher E Oct Score	20	0	61	21.000	13.681
Teacher E May Score	20	1	46	16.400	11.052
Teacher F Oct Score	7	11	44	22.857	11.936
Teacher F May Score	7	14	54	32.429	15.512

Table 4 shows descriptive statistics for the October and May exam scores separated by the teacher for each group. Table 4 shows that the October exam scores ranged from 3-61% and the May exam scores ranged from 3-84%. The overall mean exam scores for students taught by teachers in the ALEKS Group increased from October to May. This increase ranged from 7.6-18.7%. In contrast, the Non-ALEKS Group had October exam scores that ranged from 0-61% and May exam scores that ranged from 1-54%. The Non-ALEKS Group taught by Teacher E showed a decrease of 5% in mean exam scores from October to May, while the Non-ALEKS Group taught by Teacher F saw a 10% increase during that time frame. This shows that every individual class had overall mean score gains from October to May, except for the Non-ALEKS Group taught by Teacher E.

In order to test the null hypothesis, that assignment to the ALEKS PPL Pre-Calculus Learning Modules does not affect student's performance on the ALEKS Mathematics Placement Exam, we assessed assumptions before performing a 2x2 mixed ANOVA. Because the two groups' distributions had skewness and kurtosis less than |2| for both the October exam and May exam (Lomax, 2001), assumptions of normality were satisfied (Schmider, Ziegler, Danay, Beyer, & Bühner, 2010). Furthermore, Levene's *F* test of equality variances showed that both the October, $F(1, 98) = .46$, $p = .499$, and May, $F(1, 98) = 2.27$, $p = .135$, exam scores met the homogeneity of variance at the .05 significance level. Box's test of equality of covariance $M = 4.15$, $F(3, 42071.9) = 1.34$, $p = .259$, failed to find evidence of violation of this assumption.

The 2x2 mixed ANOVA showed a significant interaction between group and date, $F(1, 98) = 19.16$, $\eta\rho2 = .16$, $p < .001$. This means that there was sufficient evidence to reject the null hypotheses. Assignment to the Pre-Calculus Learning Modules did affect students' performance on the ALEKS Mathematics Placement Exam for the participants in this study, such that those students in the ALEKS group increased their exam scores between October and May, *Mdiff* = 13.55, *SE* = 1.72, $p < .001$, d = 0.87, 95% *CI* [10.14, 16.96], whereas their peers who were not assigned to use ALEKS exhibited no statistically significant change in mean performance, *Mdiff* = -0.93, *SE* = 2.83, $p = .744$. Estimated marginal mean ALEKS PPL Mathematics Placement Exam are displayed in Figure 3 including 95% confidence intervals for all means.

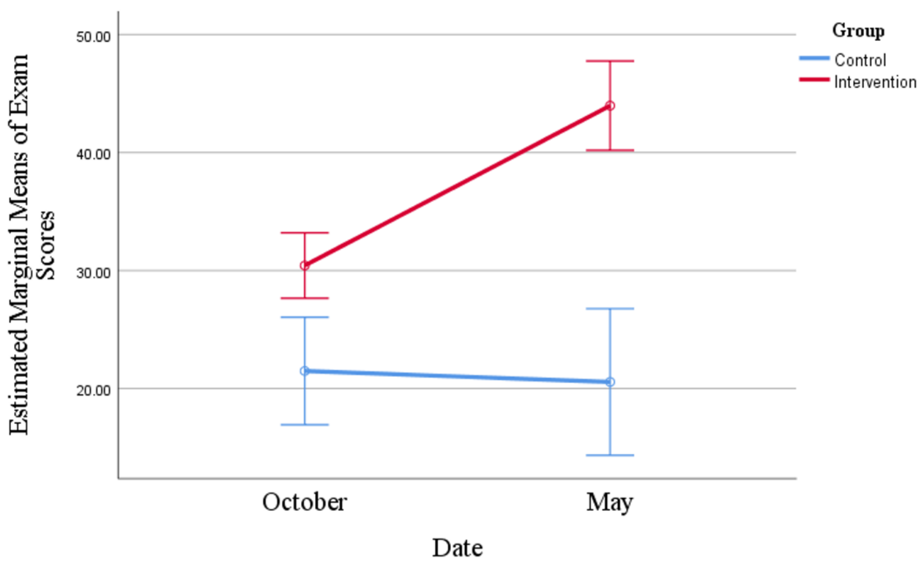

Figure 3. Estimated marginal mean from the 2x2 mixed ANOVA comparing the ALEKS PPL Mathematics Placement Exam given in October and May in both groups. (Error bars: 95% Confidence Interval)

The second research question examined the difference between the Non-ALEKS Group and the ALEKS Group in the percentage of students who scored high enough to place into College Algebra (according to the ALEKS PPL Mathematics Placement Exam). The analysis to answer this research question included summary methods and the use of logistic regression. The first analysis examined the results for the Non-ALEKS Group taught by Teacher E. Because of the decrease in mean scores experienced by the students in this group, further inspection was needed to look at exam time separated by teacher. Figure 4 shows side-by-side boxplots comparing the ALEKS Group and the Non-ALEKS Group to examine the amount of time students spent taking the Mathematics Placement Exam separated by group and teacher.

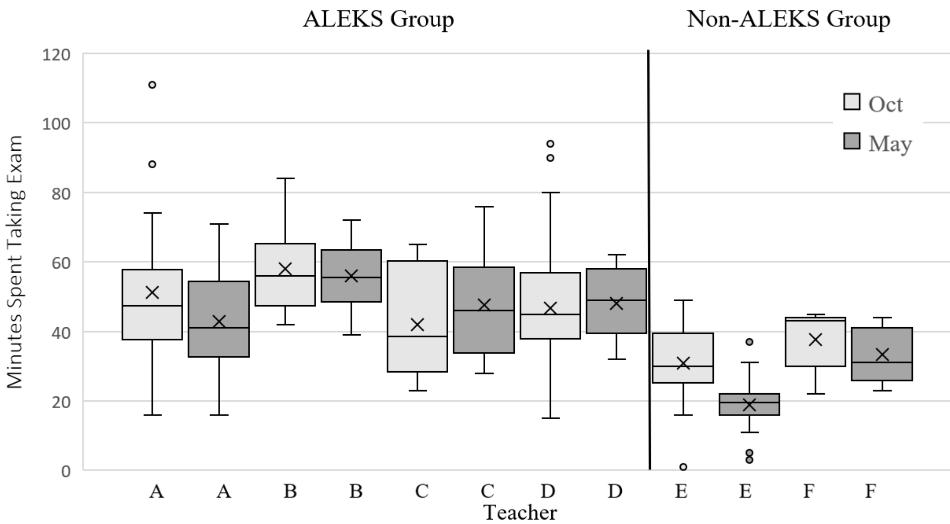

Figure 4. Boxplot of ALEKS and Non-ALEKS Group exam time separated by group and teacher.

As Figure 4 shows, all classes in the ALEKS Group are relatively similar in the amount of time students spent taking the exam in October and May. All of the students taught by teachers in the ALEKS Group had similar averages and spread between the October and May exams. The students in the Non-ALEKS Group had much lower median times on the May exam than the October exam. Additionally, the amount of time spent by the students in the class taught by Teacher E shows a significant drop-in exam time for the May exam compared to the October exam for that class, and in comparison, with all of the other classes in the study. This shows that the students in Teacher E's class spent much less time taking the May Exam when compared with all of the other classes.

The preceding figure shows that there was considerable variation in the amount of time students spent on the exam by class. There was also a decrease in exam scores from the October exam to the May exam for the students in the class taught by Teacher E. The low amount of time students spent taking the May exam likely impacted student scores. If students did not spend adequate time on the exam, it is likely that they did not perform to their true ability. Because 74% of the students in the Non-ALEKS Group were in the class taught by Teacher E, the analysis of the Non-ALEKS Group is likely to be heavily swayed by this one teacher. Figures 5 and 6 display bar graphs to show the percentage of students who qualified to register for College Algebra based on their exam scores in October and in May for the two participating groups, and a summary of student placement exam performance by teacher.

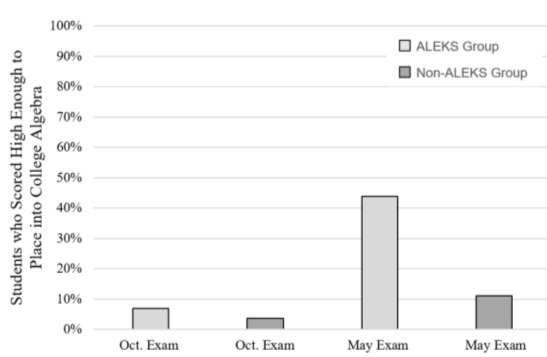

Figure 5. Percentage of students who qualified to register for College Algebra by group.

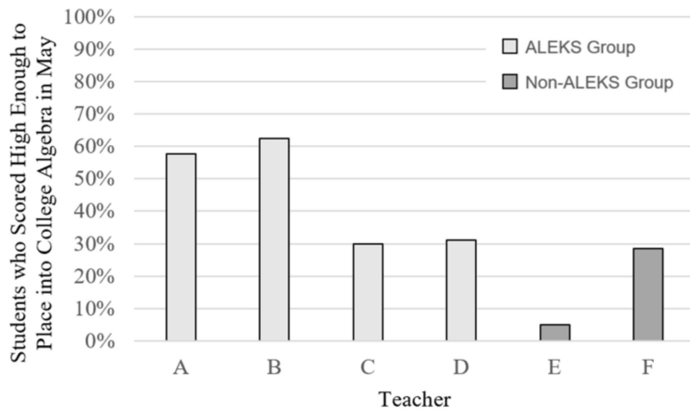

Figure 6. Percentage of students who qualified to register for College Algebra by teacher based on their May exam score.

As shown in Figure 6, two teachers in the ALEKS Group (Teacher A and Teacher B) had significantly higher percentages of students who qualified to register for College Algebra in May compared to all other teachers. Teacher F (in the Non-ALEKS Group) had a similar percentage of students who qualified for College Algebra as Teacher C and Teacher D (in the ALEKS Group). Only the students in the class taught by Teacher E performed significantly different from all other classes. The ALEKS Group had a range of percentages from 30-63% who qualified for College Algebra, while the Non-ALEKS Group had a range of percentages from 5-29% who qualified for College Algebra, which is much lower than the ALEKS Group.

To examine this phenomenon, we conducted a logistic regression analysis to investigate the difference between the Non-ALEKS Group and the ALEKS Group in the percentage of students who scored high enough to place into College Algebra (Score ≥ 46%) according to the ALEKS PPL Mathematics Placement Exam. The continuous predictor variables, including time students spent taking the May exam (minutes) and initial placement exam score (from October), were tested to verify that there was no violation of the assumptions of linearity of the logit. Because the interaction terms were not significant, the main effect did not violate the assumptions of linearity of the logit (Field, 2013). Additionally, collinearity statistics showed a tolerance greater than .1 and VIF less than 10, which does not indicate a problem for collinearity for all predictor variables (Field, 2013). Table 5 shows the collinearity diagnostics, which provide eigenvalues and variance proportions to investigate the possibility of multicollinearity.

Table 5: Collinearity Diagnostics with the Dependent Variable Cut-Score and the Three Predictor Variables: Group, May Exam Time, and October Score

				Variance proportions			
Model	**Dimension**	**Eigenvalue**	**Condition index**	**(Constant)**	**Group**	**May exam time**	**Oct Score**
1	1	3.686	1.000	0.010	0.010	0.010	0.010
	2	0.173	4.621	0.100	0.510	0.010	0.190
	3	0.089	6.432	0.500	0.050	0.050	0.800
	4	0.052	8.419	0.390	0.440	0.940	0.000

The Eigenvalues in Table 5 are relatively close which does not indicate a problem with collinearity (Field, 2013). If the variance proportions have any predictors that contain large proportions on the same small eigenvalue, then this would indicate that the variance of their regression coefficients are dependent (Field, 2013). Table 5 shows, for the predictor variable Group, that 44% of the variance of the regression coefficient is associated with eigenvalue number 4. Additionally, for the predictor variable May exam time, 94% of the variance of the regression coefficient is associated with this same eigenvalue. This shows that there may be collinearity among the variables Group and May exam time.

The outcome of interest for Research Question 2 was if students' scores were at least 46%. The possible predictor variables to test for this outcome were Group (ALEKS or Non-ALEKS), May exam time, and October exam score. Additionally, the Hosmer-Lemeshow goodness-of-fit test was not significant ($p > .05$) indicating that the model was correctly specified (Field, 2013). These variables together accounted for about 39% of the variance (Nagelkerke R square = .391). The model resulted in the independent variables, Group ($p = .326$) and May exam time ($p = .178$) not being significant.

However, the independent variable, October exam score, was found to be significant. Controlling for Group and May exam score, the predictor variable, October exam score, in the logistic regression analysis was found to contribute to the model. The parameter estimate unstandardized $b = 0.095$, $SE = 0.026$, $t(1) = 12.99$, $p < .001$. The estimated odds ratio favored a positive relationship, $OR = 1.100$, 95% CI [1.04, 1.16]. This shows a relationship between October exam scores and scoring at least 46% on the exam in May. This means that if a student's October exam score increases by 1%, then they are 10% more likely to score at least a 46% on the May exam. A logistic regression for group alone and group with May exam time was analyzed next, because diagnostics showed the possibility of multicollinearity.

The analysis for the logistic regression with Group as the only predictor variable had a significant Hosmer-Lemeshow goodness-of-fit test ($p < .001$), therefore this model was a poor fit. The independent variable, Group, was found to be significant and would have contributed to the model if the model had been a good fit. The parameter estimate unstandardized $b = -1.83$, $SE = .66$, $t(1) = 7.79$, $p = .005$. The estimated odds ratio shows that students in the ALEKS Group were 6.25 more likely to score at least 46% on the ALEKS Mathematics Placement Exam compared to the Non-ALEKS Group, $OR = 0.16$, 95% CI (0.04, 0.58).

Next, we analyzed the logistic regression with the predictor variables Group and May exam time. The Hosmer-Lemeshow goodness-of-fit test was not significant ($p > .05$) indicating that the model was correctly specified (Field, 2013). These variables together accounted for about 21.1% of the variance (Nagelkerke R square = .201). The predictor variable Group was not significant ($p = .265$). However, the independent variable, May exam time, was found to be significant. Controlling for Group, the predictor variable, May exam time, in the logistic regression analysis was found to contribute to the model. The parameter estimate unstandardized $b = 0.04$, $SE = 0.02$, $t(1) = 4.83$, $p = .028$. The estimated odds ratio favored a positive relationship, $OR = 1.04$, 95% CI [1.01, 1.08], such that the odds for students' scores to be equal to at least 46% increases by 4% for every 1-minute increase of May exam time.

These results indicated that the October exam score was a predictor of students' May exam score being high enough to place into College Algebra. The results also showed that May exam time was a predictor of students' scores to be at least 46%. However, there was no evidence that group assignment (ALEKS or Non-ALEKS) was a predictor of placing into College Algebra.

Discussion

The results of the first research question showed a significant interaction between group (ALEKS Group or Non-ALEKS Group) and the date students completed the exam (October or May). The limitations of the study prevent the conclusion that assignment to the ALEKS PPL Learning Modules did affect student performance on the ALEKS Mathematics Placement Exam. One reason to consider the results with caution was the effect of Teacher E, who showed significant disengagement with the ALEKS program and this study. A careful review of the results revealed that the students taught by Teacher E, who taught 74% of the Non-ALEKS Group, had similar scores on the October exam compared to all other classes. Conversely, those same students scored significantly lower on the May exam compared to all other classes, even other students in the Non-ALEKS Group. A closer examination showed that students taught by Teacher E spent far less time taking the May exam compared to the other groups of students.

The students that worked with the Intelligent Tutoring System experienced more growth on the ALEKS Mathematics Placement Exam than students in the Non-ALEKS Group. The students in the ALEKS Group had the opportunity to have individualized mathematics practice and be exposed to the expected mathematics in the college curriculum.

The results of the second research question showed that October exam scores were a predictor of scoring at least a 46% on the May placement exam. Students were 10% more likely to score at least 46% on the May exam for every 1% increase in their October exam score. Although Group was not a predictor of scoring at least 46% on the May exam, May exam time was a predictor. This showed that the more time students spent on the May exam, the higher the scores were to be expected.

Providing students with adequate time to take the exam, and providing an incentive for student effort, was important for students to realize actual placement scores. The ALEKS Group experienced a 43.8% placement rate while the Non-ALEKS Group had an 11.1% placement rate. Two teachers (Teachers A and B) in the ALEKS Group had over 50% of their students place into College Algebra while Teachers C and D in the ALEKS Group had placement rates similar to Teacher F (29-31%) in the Non-ALEKS Group. Teacher E had only 5% of their students score high enough to place into College Algebra.

In this study, 6.1% of the variance in the difference of exam scores was accounted for by the difference in exam time between October and May. The teachers who taught the students in the ALEKS Group all used the May exam as part of students' grades, which could have motivated the students to spend a little more time and try harder on the exam. These results are consistent with the recommendation by the ALEKS Corporation to assign a grade value to the program to incentivize students to put forth more effort (Advanced Customer Solutions, ALEKS Corporation, 2017).

Most teachers reported that implementing ALEKS into their classroom was easy and beneficial. In contrast, Teacher A, said they would not implement ALEKS PPL into their classroom ever again because there were too many problems with students forgetting passwords and not knowing how to gain access to the program. Teacher B expressed that filling gaps in students' knowledge through the use of ALEKS PPL benefited the students. Research by Karner (2017) found that students who used ALEKS in a remedial setting were able to close the gap between low achieving students and those who were not by 30.4%.

All teachers in the ALEKS Group reported to the researchers that they believed students benefited from the use of ALEKS PPL and that the students who used the program as instructed increased their May exam scores. The amount of time students spent working with technology can affect student outcomes. For example, Cheung and Slavin (2013) found that educational technology programs were more effective if they required more than 30 minutes per week when compared with those that were used less than 30 minutes per week. The ALEKS Corporation recommends using the program at least three hours per week for effective implementation (Advanced Customer Solutions, ALEKS Corporation, 2017). If teachers do not support the program, students are less likely to spend the recommended amount of time with the technology (Cheung & Slavin, 2013).

Conclusion

This study examined relationships between high school students' performance in the ALEKS PPL Modules and performance on the ALEKS College Mathematics Placement Exam. The results showed a statistically significant difference in exam scores between the ALEKS Group and the Non-ALEKS Group, with the ALEKS Group participants in this study having greater increases in performance on the ALEKS College Mathematics Placement Exam. The probability of placing into College Algebra was attributed to the initial score on the October placement exam and the amount of time students spent taking the exam in May. Students were 10% more likely to score at least 46% on the ALEKS Mathematics Placement Exam for every 1% increase in their October placement exam score.

If schools can effectively implement ALEKS into their current mathematics classrooms, there is the potential to strengthen students' preparation for college level mathematics. By increasing students' scores on the ALEKS Mathematics Placement Exam, students are potentially decreasing the likelihood of taking remedial courses in college. However, limitations including the small sample size, non-randomized placement, testing effects, and lack of teacher engagement, need to be considered in the interpretation of these results.

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