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Student success in intelligent tutoring systems: An assessment of key factors

Jenny Nehring, *Utah Valley University, jenny.nehring@uvu.edu*
George D. Hickman, *Utah Valley University, ghickman@uvu.edu*

Abstract

Artificial Intelligence–based Intelligent Tutoring Systems (ITS) have been used to help high school students better prepare for college-level mathematics. The purpose of this study is to determine which factors positively influence student outcomes on the college mathematics placement exam for students assigned to work on the Assessment and Learning in Knowledge Spaces (ALEKS) ITS modules. Seventy-three students from three U.S. high schools participated in the study. Variables including students' exam scores, time spent logged into ALEKS modules, time spent completing the placement exam, teacher assigned, and module mastery scores (both pre- and post-module completion) were analyzed to test for significant differences. A multiple linear regression was used to determine which factors influenced growth on the ALEKS Mathematics Placement Exam. The results indicated that the amount of time students spent taking the placement exam and the number of modules mastered were significant predictors of exam performance. These findings suggest that schools emphasizing these factors could use AI/ITS in current courses to help students bypass developmental mathematics and directly enroll in college-level math upon entering college.

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

Introduction

This study examines the extent to which various factors (module time, module mastery scores, teacher, exam score) within Assessment and Learning in Knowledge Spaces (ALEKS) positively influence student scores on the ALEKS College Mathematics Placement Exam. Intelligent Tutoring Systems (ITS) are educational tools that use concepts from several disciplines such as artificial intelligence (AI), cognitive science, computational linguistics, education, and mathematics (Graesser et al., 2012; Troussas et al., 2024). Due to the mismatch between the high school mathematics preparation and students' college level readiness in mathematics (Conley, 2003), ITS programs such as the ALEKS Placement, Preparation, and Learning (PPL) system have been created and are widely used in secondary schools (Oxman and Wong, 2014). Federal grants provided to universities funded several initial efforts to design ITS programs to provide one on one type tutoring for public K through 12 schools (Oxman et al., 2014). Each learner's preparation is cognitively diagnosed (modeled) by the ITS to provide individualized instruction and adaptive remediation (Ma et al., 2014).

Although ALEKS is designed to function without teacher intervention, the teacher's classroom practices may still influence how students interact with the system. Examining how students engage with ITS tools such as ALEKS in different classroom contexts may provide insight into the role these systems can play in preparing students for college level mathematics. This study will highlight factors that increase the effectiveness of these Intelligent Tutoring Systems (ITS) when utilized.

Research Question

This study explores the effectiveness and utility of an Intelligent Tutoring System (ITS) by addressing the following question:

What factors (module time, module mastery scores, teacher, exam score) positively influence student outcomes on the college mathematics placement exam for those assigned to work on the ITS modules?

Literature Review

Research on Intelligent Tutoring Systems (ITS) has expanded in recent years, particularly in the context of mathematics readiness and college placement. This review examines existing literature related to the development and functionality of ITS tools such as ALEKS, their role in addressing gaps between high school and college level mathematics, and the conditions under which these tools have demonstrated effectiveness. The review also identifies limitations in prior studies and considers broader applications of ITS across academic subjects.

Bridging the Gap Between High School and College Mathematics

This study explores the use of ALEKS PPL as a supplementary tool in high school mathematics instruction to help bridge gaps between high school and college-level mathematics. Despite significant advancements in American education over the past century, a gap remains between high school mathematics preparation and college-level readiness. Many students graduate from high school only to find themselves underprepared for the rigors of college coursework (Barnett et al, 2013; Bettinger et al., (2013); Hilgoe et al., (2016). Research has shown a gap in what high school math teachers believe is needed for college readiness and what college math professors expect from incoming students (Er, 2017; Godfrey, 2020). While the extent of this issue varies nationwide, approximately 60% of incoming college students require remedial coursework (Bailey, 2009; Barnett et al., 2013; NCPPHE & SREB, 2010; Barnett, Chavarin and Griffin, 2018). Research from Strong American Schools (2008) indicates that the majority of students placed in remedial classes were considered strong performers in high school, with nearly 80% reporting a GPA of 3.0 or higher. These findings suggest that even students with solid academic records often lack the mathematical foundation necessary for success in college-level courses.

Studies have demonstrated that technology can positively influence mathematics learning, particularly when implemented through ITS platforms (Craig et al., 2013). Research has consistently shown that students who engage with ITS in mathematics classrooms exhibit improved performance on assessments measuring college readiness (Craig et al., 2013; Fine et al., 2009; Haulket al., 2015; Sabo et al., 2013). However, a key limitation in existing research is the lack of full academic-year studies comparing ITS-supported classrooms to those without ITS integration over the same period. Addressing this gap would provide a more comprehensive understanding of how ITS influences long-term student outcomes and its potential role in mathematics education reform.

Development and Function of Intelligent Tutoring Systems

The introduction of Intelligent Tutoring Systems (ITS) in public schools was largely facilitated by government funding (McGraw-Hill Education, 2020a; Oxman et al., 2014). In 1992, a major grant from the National Science Foundation (NSF) supported the development of educational software rooted in

Knowledge Space Theory, leading to the creation of ALEKS (McGraw-Hill Education, 2020a). ITS programs, such as ALEKS PPL, offer significant potential for enhancing mathematics instruction in K-12 education by personalizing learning experiences. ALEKS assesses students' knowledge and constructs an individualized learning path within the knowledge space to optimize their progress (ALEKS, 2018a). As an ITS, ALEKS tailors instructional content based on student performance, continuously tracking progress and administering periodic knowledge checks to reinforce retention (Fine et al., 2009).

Intelligent Tutoring Systems (ITS) have become a major focus for commercial product developers, with significant investments directed toward creating adaptable, self-paced learning platforms that support mathematics remediation. These systems tailor instructional content to individual learners, dynamically adjusting learning plans to meet their specific needs (Ma et al., 2014; Steenbergen-Hu & Cooper, 2013, Chen, Yang, 2025). While ITS cannot replace the role of a teacher in the classroom, and simply integrating technology does not automatically lead to improved student performance, research suggests that these systems can play a valuable role in enhancing college readiness for mathematics (Craig et al., 2013; Fine et al., 2009; Sabo et al., 2013; Haulk, et al., 2015). Given the increasing demand for effective strategies to bridge the gap between high school and college-level mathematics, further exploration into the impact of ITS on student preparedness is needed.

Design Considerations and Broader Impact of ITS

The effectiveness of an Intelligent Tutoring System (ITS), such as the ALEKS PPL program, depends heavily on best practices in implementation, as numerous factors influence student outcomes. Variables such as student attitudes, teacher support, and time spent using the system all play a role in its success. Cheung and Slavin (2013) found that educational technology programs requiring more than 30 minutes of use per week were significantly more effective than those used less frequently.

Technology designed for mathematics education can generally be classified into two categories: tools for skill practice and tools for conceptual development. Tools focused on conceptual development emphasize helping students construct meaning, recognize patterns, and develop deeper epistemological awareness (Hoyles et al., 2004). Conceptual understanding is often characterized by the relationships and connections between mathematical ideas, and technology serves as a powerful medium for illustrating these relationships (Heid & Blume, 2008). In contrast, skill-practicing tools are structured to provide systematic practice, immediate feedback, and guided tutorials to support student learning (Drijvers et al., 2017). The ALEKS PPL program, along with most ITS platforms, falls primarily within the skill-practicing category, as it focuses on reinforcing procedural fluency and mastery through individualized instruction and adaptive learning paths. Additional studies evaluating the effectiveness of Intelligent Tutoring Systems in other subject areas, such as reading comprehension, have shown similarly positive results (Wijekumar et al., 2024; Xu et al., 2019). These findings suggest that the adaptive, feedback-driven structure of ITS platforms may offer broad educational benefits across content areas, reinforcing the value of continued research into their role in both literacy and mathematics education.

Methodology

This study employs a quasi-experimental design to examine the relationship between high school students' engagement with ALEKS Modules and their performance on the ALEKS PPL Mathematics Placement Exam. Data collection was conducted under an approved IRB protocol (#9350) and has also been utilized in prior research addressing different research questions (Nehring, J., Moyer-Packenham, P., & North, M., 2023). Students participated in traditional mathematics instruction supplemented with ALEKS PPL

Modules throughout the academic year. To assess changes in performance, students completed the ALEKS PPL Mathematics Placement Exam at both the beginning (October) and end (May) of the school year.

The participants were 73 high school students, ages 16-18 who were enrolled in 6 different class sections of College Prep Mathematics during their senior year of high school. Three different high schools participated in the study. Table 1 presents the distribution of schools, classes, teachers, and participants in the study. The quantitative data sources and measurements that are used for this study include: Student scores on ALEKS PPL Mathematics Placement Exam (initial score in October's pre-test and final score in May's post-test), student module mastery scores on ALEKS PPL Pre-Calculus Learning Modules, and time data recorded for student time logged into ALEKS PPL modules. The data is analyzed using multiple linear regression, along with descriptive statistics. This method was selected because it allowed for the analysis of how multiple independent variables jointly influenced a continuous dependent variable, while accounting for the unique contribution of each predictor.

Although this study used a quasi-experimental design, several steps were taken to manage potential bias. The inclusion of multiple high schools and teachers across six different class sections helped provide variation in instructional settings. All students used the same ALEKS PPL modules and placement exam, which ensured consistency in instructional materials and outcome measures. Teacher was included as an independent variable in the regression analysis to account for possible classroom-level effects. And finally, the use of both a pretest and a posttest allowed each student to serve as their own control, which helped account for individual differences in prior knowledge.

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

Location	Number of classes	Number of teachers	No. of participants in each class	Total no. of participants
High School A	3	2	4, 22, 8	34
High School B	1	1	10	10
High School C	2	1	21, 8	29
TOTALS	**6**	**4**		**73**

The ALEKS PPL Mathematics Placement Exam student scores is the first measure of student performance. The state of the students' current knowledge is assessed by the ALEKS PPL Mathematics Placement Exam; this data is used to create an instructional plan to teach students topics that they are most ready to learn (McGraw-Hill Education, 2020b; Yilmaz, 2017). The one-hour exam asks 30 questions from 314 interrelated mathematics topics.

The second measure is the ALEKS PPL module mastery scores. This data came from the ALEKS PPL Pre-Calculus Learning Modules. The Pre-Calculus learning modules have 246 topics divided among eight problem types. There are two types of module mastery scores: Initial Mastery Scores (which indicate initial mastery of module topics learned) and Final Mastery Scores (which indicate final mastery of module topics learned). Each student will have two items of log data: (1) the number of initial topics mastered, and (2) the final number of topics mastered.

The third measure is time data. There were two types of time measures. One measure of time, based on the ALEKS PLL Learning Modules, is the cumulative amount of time students spent logged in to the Pre-Calculus Learning Modules (called "module time"). The other measure of time is based on the ALEKS PPL Placement Exam. This is the amount of time students spent taking each exam (called "exam time"). The "module time" data was collected throughout the academic school year each time the student logged in, either at home or at school. 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 in the modules or taking the exam is related to their exam scores. Table 2 outlines the research question, corresponding measures, and the data analysis methods used in this study.

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

Research question	Measures	Data analyses
What factors (module time, module mastery scores, teacher, exam score) influence student outcomes on the college mathematics placement exam for those assigned to work on the ITS modules?	ALEKS Mathematics Placement Exam scores October and May; Log data on exam time and cumulative module time; Final module mastery scores	Multiple Linear Regression **DV**= exam growth over time (continuous exam score difference, May's post-test minus October's pre-test) **IV1** = difference in exam time taken (May – October, continuous minutes) **IV2** = difference in module mastery scores (continuous, percentage) **IV3** = cumulative module time (continuous, minutes) **IV4** = teacher (4 different teachers, **ID** = 1, 2, 3, 4)

Factors that Influence Student Outcomes Analysis

Multiple linear regression is used to address the research question which focuses on potential factors that influenced students' growth on the ALEKS PPL Mathematics Placement Exam. This analysis included all students (n=73) assigned to use the Pre-Calculus Learning Modules. The dependent variable was defined as the difference in ALEKS PPL Mathematics Placement Exam scores in October and May. The independent variables were the difference in the amount of time spent working on the ALEKS PPL Mathematics Placement Exam (May exam time – October exam time spent in minutes), the difference in the percentage of topics mastered in the ALEKS PPL Pre-Calculus Learning Modules (final module mastery scores – initial module mastery scores), the amount of time logged into the ALEKS PPL Pre-Calculus Learning Modules (cumulative module time in minutes), and the teacher assigned to each student group (ID = 1, 2, 3, 4). In the regression model, the variable "teacher" is treated as a categorical variable with multiple levels, with each teacher (A, B, C, and D) representing a distinct group. Teacher C was used as the reference category, so the regression coefficients for Teachers A, B, and D reflect how their students' outcomes differ in comparison to those of Teacher C.

This study began with exploratory data analysis, including the calculation of summary statistics such as mean, median, standard deviation, and range, along with scatterplots and correlation coefficients to examine bivariate relationships. A Wald test was used to assess the statistical significance of the independent variables, and variance inflation factors (VIF) were examined to identify any potential multicollinearity among predictors in the regression model.

Results

The research question examined the factors (module time, module mastery scores, teacher, exam time) that may have influenced student outcomes on the Mathematics Placement Exam between the October and May exams for the participants. The analyses to answer this research question included summary methods and a multiple linear regression. For example, Figure 1 shows a boxplot of the dependent variable, with the difference in exam scores from October to May, for teachers participating in the study. This was found by subtracting each student's October exam score from their May exam score. Most students show a gain, but some experienced a loss, indicated by a negative percentage.

The mean and median scores for the students taught by Teachers A, B, and C are all very similar across classes, as shown in Figure 1. Scores for students taught by Teacher D have a mean and median lower than the other teachers in the group.

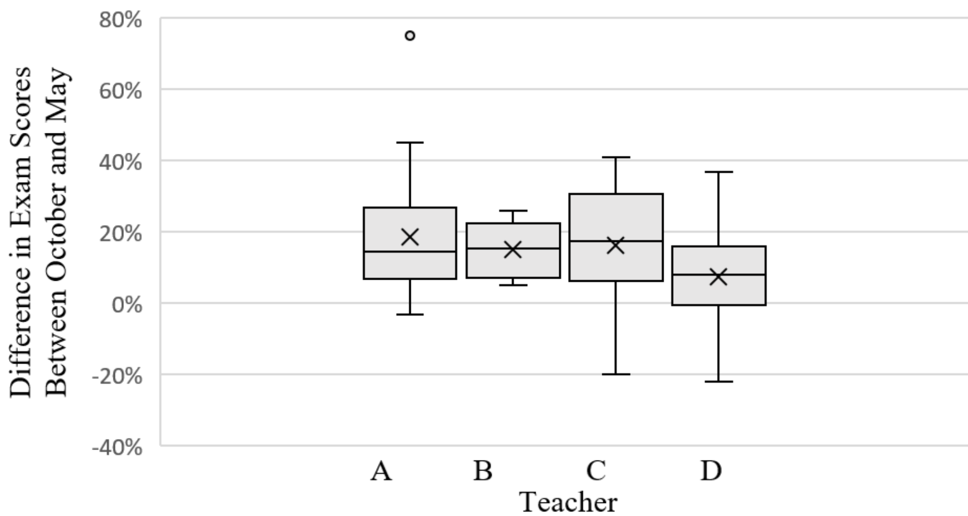

Figure 1. Difference of exam scores by the teacher.

Notably, Teacher B's students all demonstrated gains, with a relatively narrow range of outcomes. In contrast, Teachers C's and D's groups exhibited wide ranges, suggesting greater variability in student progress. Table 3 shows the descriptive statistics for the difference in exam scores.

Table 3. Descriptive Statistics of Difference in Exam Scores Separated by Teacher

Teacher	n	Min	Max	Mean	SD
A	26	-3.000	75.000	18.769	16.929
B	8	5.000	26.000	15.125	7.990
C	10	-20.000	41.000	16.200	17.825
D	29	-22.000	37.000	7.517	13.574

As Table 3 shows, all of the students taught by Teacher B experienced gains on their post-test exam. The lowest student taught by Teacher A had a loss of 3%, while those taught by Teachers C and D had up to a 22% loss. Students taught by Teacher A had the highest overall mean gain of 19%, which was similar to the other teachers except for students taught by Teacher D, who had a mean gain of 8%.

Figure 2 displays a boxplot of the difference in the amount of time students spent taking the exam from the October to the May exam for all students that participated. This was found by subtracting the time it took each student to take the October exam from the time it took each student to take the May exam. The figure shows that many students took the May exam in less time, and this is shown by a negative time. The difference in exam time is one of four independent variables that will be used in the multiple linear regression.

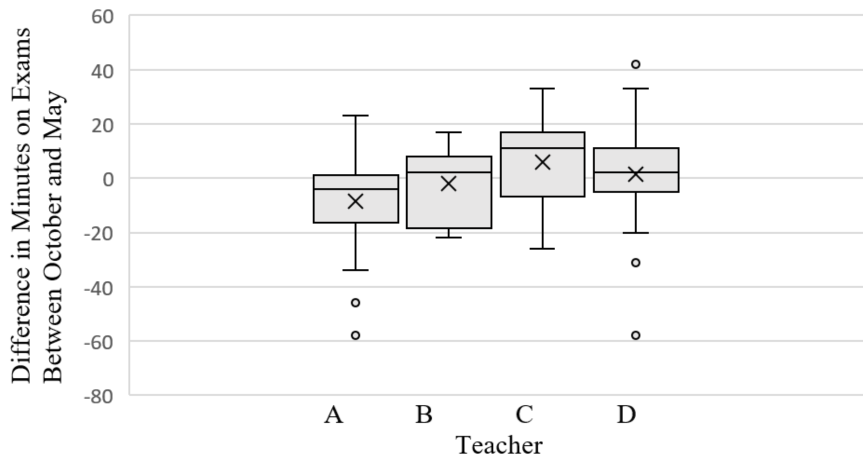

Figure 2. Boxplots of difference in exam time in minutes.

Figure 2 highlights that the students taught by Teacher C had the greatest average difference in exam time with a positive mean and median difference. This means that students in this class on average took longer on the May exam than the October exam. All of the others experienced a negative or close to zero difference. Table 4 shows the descriptive statistics of the difference in exam time for all of the teachers in the study.

Table 4. Descriptive Statistics of Differences in Exam Time by Teacher

Teacher	*n*	Min	Max	Mean	*SD*
A	26	-58.000	23.000	-8.423	18.446
B	8	-22.000	17.000	-2.125	14.407
C	10	-26.000	33.000	5.800	17.008
D	29	-58.000	42.000	1.379	19.083

As shown in Table 4, the students taught by Teacher A, on average, decreased the amount of time spent on the post-test by 8.42 minutes. Conversely, the students in Teacher C's class increased on average by 5.80 minutes. The standard deviations are roughly the same for all classes, with two classes decreasing the average amount of time spent on the post-test and two classes increasing the amount of time.

Figure 3 graphs the differences in the percentage of topics mastered separated by the teacher. This is found by subtracting the percentage of topics mastered at the beginning of the year from the percentage of topics mastered at the end of the year.

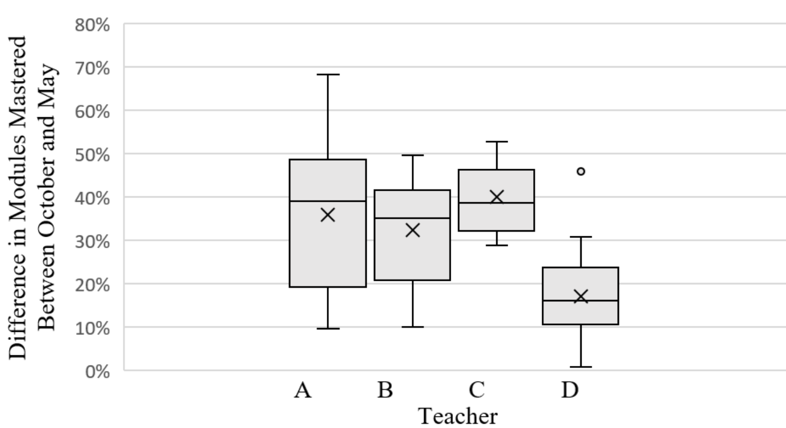

Figure 3. Differences in the percentage of topics mastered separated by teacher.

Students taught by Teachers A, B, and C all had similar means and medians for the difference in the percentage of topics mastered in the modules. Students taught by Teacher D on average mastered far fewer topics than all of the other classes.

Table 5 contrasts the descriptive statistics for differences in modules mastered separated by the teacher. This was computed by subtracting the percentage of number of topics mastered in October exam from the percentage of number of topics mastered in the May exam. The average percentage of topics mastered between the October exam and May exam for students taught by Teachers A, B, and C ranged from 33% to 40%. In comparison, students taught by Teacher D averaged only 17%, indicating that they mastered roughly half as many topics as their peers by the end of the year.

Table 5. Differences in Percentage of Topics Mastered from October exam to May exam by Teacher

Teacher	*n*	Min	Max	Mean	*SD*
A	26	10.000	68.000	36.039	17.224
B	8	10.000	50.000	32.500	13.234
C	10	29.000	53.000	40.200	7.800
D	29	1.000	46.000	17.172	9.864

To better understand how engagement with the learning modules varied by teacher, the total number of minutes each student spent logged into the ALEKS Pre-Calculus Learning Modules was examined. Figure 4 displays this information, grouped by teacher.

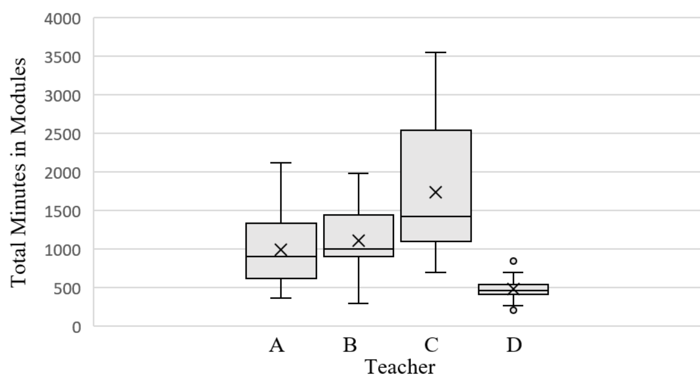

Figure 4. Number of minutes students spent logged into the learning modules.

Figure 4 shows that students taught by Teacher D spent significantly less time in the modules compared to students taught by Teachers A, B, and C. The range of time spent is also notably narrower for Teacher D's group, with relatively little variation among students. In contrast, Teacher C's group exhibited the widest spread in total time, indicating a broader range of engagement. The students taught by Teachers A and B had similar median and mean times, suggesting more consistent engagement levels across those two groups. Table 6 presents module login time descriptive statistics grouped by teacher.

Table 6. Descriptive Statistics of Number of Minutes Students Spent Logged into the Learning Modules from October exam to May exam

Teacher	*n*	Min	Max	Mean	*SD*
A	26	364.000	2123.000	991.192	445.111
B	8	303.000	1988.000	1108.875	492.346
C	10	697.000	3557.000	1738.500	941.167
D	29	210.000	904.000	482.207	161.861

As show in Table 6, students taught by Teacher D logged in to the modules less than half the number of minutes of any other teacher. The students taught by Teacher C averaged the most time with 1,738.5 minutes (almost 30 hours). Students in Teacher B's class followed with 1,108.9 minutes (about 18.5 hours). Students taught by Teacher A logged in 991.2 minutes (about 16.5 hours) and students in Teacher D's class logged in 482.2 minutes (about 8 hours).

Table 7 presents the correlations between the variables, followed by scatterplots that illustrate the bivariate relationships between the dependent variable and each independent variable.

Table 7. Correlations Between Variables for Students in the ALEKS Group

Variable	Diff. exam scores	Diff. exam time	Diff. module score	Module time
Diff. exam scores	-	.246*	.564**	.331**
Diff. exam time	.246*	-	.061	.052
Diff. module score	.564**	.061	-	.599**
Module time	.331**	.052	.599**	-

Note. Diff. = Difference; *p < .05, **p < .01.

We see in Table 7 that there is a weak positive correlation between difference in exam scores and difference in exam time, $r(71) = .246$, $p < .05$, and there is a strong positive correlation between the difference in exam scores and difference in module score, $r(71) = .564$, $p < .01$. There is also a moderate positive correlation between the difference in exam scores and module time, $r(71) = .331$, $p < .01$. This indicates that mastering more topics is strongly related to higher exam scores while spending more time in the modules is moderately related to higher exam scores. The scatterplot in Figure 5 shows this weak positive correlation between change in exam time and change in exam scores, with considerable variability among students.

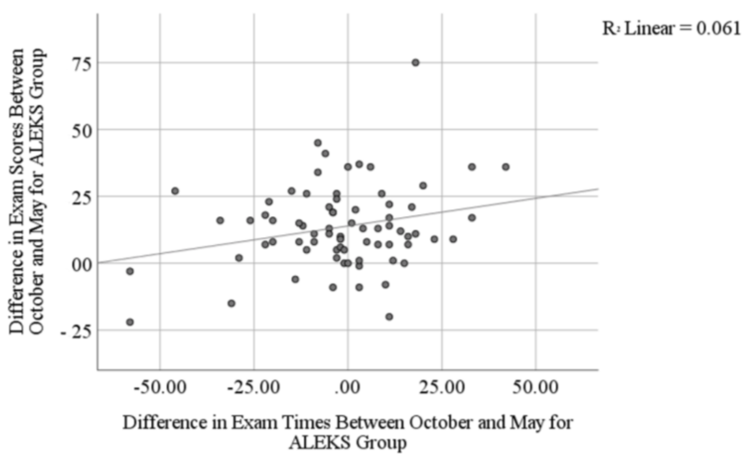

Figure 5. Scatterplot of the correlation between the difference in exam scores and difference in exam time.

Figure 5 shows the relationship between differences in exam scores and the difference in the amount of time spent on the exams; the correlation between the difference in exam scores and the difference in exam time for students in the ALEKS Group is very weak. This shows that 6.1% of the variance is being accounted for in the difference in exam scores from the difference in the amount of time students spent taking the exam. It is a small positive correlation.

Next, Figure 6 shows the relationship between differences in exam scores and the difference in the percentage of topics mastered.

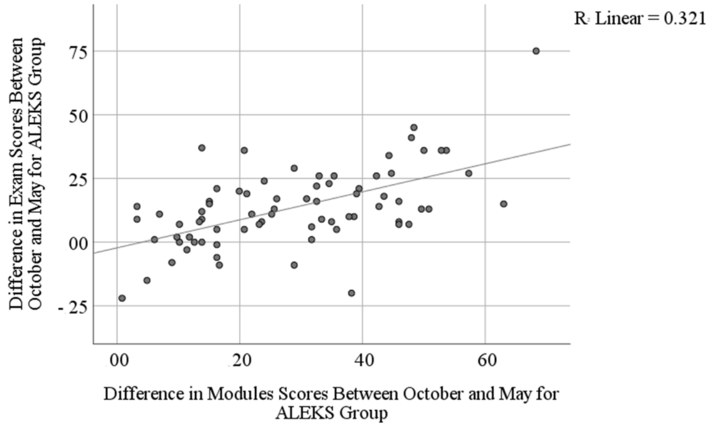

Figure 6. Scatterplot of the correlation between the difference in exam scores and difference in module mastery scores.

We can see that there is a strong positive correlation between the difference in exam scores and the difference in module mastery scores. This shows that 32.1% of the variance is being accounted for in the difference in exam scores from the difference in module mastery scores. Overall, as students mastered more topics, their exam scores increased.

Figure 7 plots the relationship between differences in exam scores and the amount of time spent in the modules. This accounts for all time logged into the modules only and should not be interpreted as time spent by students working in the modules. There is a moderate positive correlation between the difference in exam scores and time spent logged into the modules for students in the study.

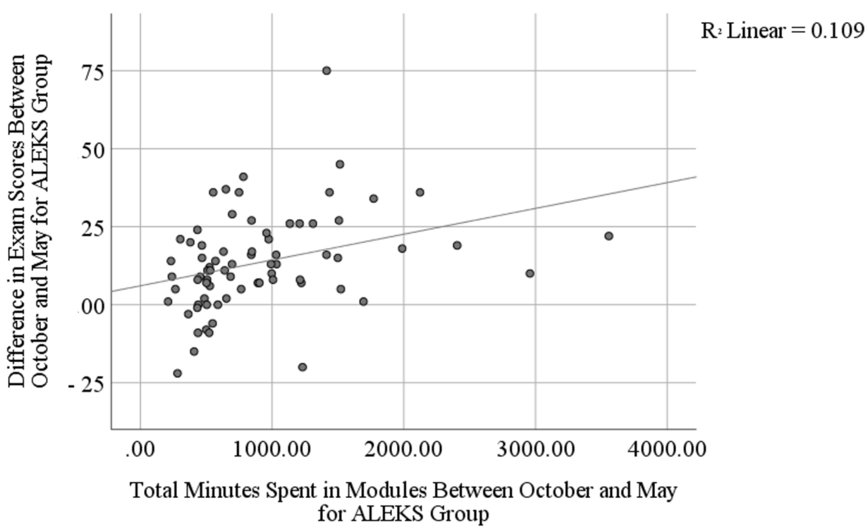

Figure 7. Scatterplot of the correlation between the difference in exam scores and time spent logged into the modules.

This shows that 10.9% of the variance is accounted for in the difference in exam scores from the time spent in the modules. Only students who spent less than 600 minutes (10 hours) saw a decrease in exam scores from the October exam to the May exam, except for one student who saw a decrease at 1,231 minutes (about

20.5 hours). Only 12.3% of the students (n = 9) in the ALEKS Group had a decrease in exam scores from October to May.

To further examine this question, the researchers conducted a multiple linear regression analysis to investigate the potential factors that influenced students' growth on the ALEKS PPL Mathematics Placement Exam. It was hypothesized that differences in the amount of time spent taking the ALEKS Mathematics Placement Exam from the October to May, the difference in the percentage of topics mastered in the ALEKS PPL Learning Modules, the Teacher students were assigned to, and the amount of time logged into the ALEKS PPL Learning Modules would positively predict the difference in exam scores.

Results show that 39.1% of the variation in the difference of exam scores can be accounted for by the predictor variables, collectively, $F(6, 66) = 7.05$, $p < .001$. This analysis used the students in Teacher C's class as the reference category. Looking at the unique individual contributions of the predictors, the results indicate that the difference in exam time, $b = 0.22$, $t(1) = 2.54$, $p = .013$, and differences in module mastery scores, $b = 0.49$, $t(1) = 3.83$, $p < .001$, positively predict differences in exam scores. The predictor variable of time spent in the modules did not have a significant effect on the difference in exam scores, $b < 0.01$, $t(1) = 0.52$, $p = .603$. Teacher A's students experienced a non-significant impact, $b = 9.10$, $t(1) = 1.67$, $p = .101$, along with Teacher B's and Teacher D's students, $b = 5.62$, $t(1) = 0.88$, $p = .382$, and $b = 5.98$, $t(1) = 0.95$, $p = .34$, respectively.

The results suggest that the factors of exam time and module mastery scores influenced students' outcomes. Students who took more time on the final exam in May, compared to their October time, and who mastered more topics in the ALEKS PPL Learning Modules, scored higher on the ALEKS Mathematics Placement Exam at the end of the academic year.

Discussion

The results of the research question showed that 39.3% of the variation in the difference of exam scores could be accounted for by the four predictor variables, which included the difference in the amount of time spent taking the exams, the difference in module mastery scores, the amount of time students were logged into the modules, and the teacher. Two of the four predictor variables, the difference in the amount of time spent taking the exam and the difference in module mastery scores, proved to be significant in positively predicting differences in exam scores. In the present study, 32.1% of the variance in the difference of exam scores was accounted for by the difference in module mastery scores.

The multiple linear regression did not find the time spent logged into the modules to be a significant predictor. One limitation of this measure is that ALEKS records time based on how long students are logged in, regardless of whether they are actively working or idle. This limits the usefulness of this variable as a proxy for true engagement. Additionally, some teachers awarded credit simply for time spent logged in, rather than for module progress, which may have further reduced the accuracy of this variable. Previous research by Bartelet et al. (2016) has shown that students are generally not self-motivated to engage with ITS unless usage is required, which may also contribute to inconsistencies in how time data reflects genuine effort.

The difference in exam time (comparing October exam and May exam time) accounted for 6.1% of exam score variance. In accordance with ALEKS Corporation recommendations, the students' post-test scores were used as part of their course grades. This likely encouraged students to take the second exam more seriously, spending more time and exerting greater effort (Advanced Customer Solutions, ALEKS Corporation, 2017).

This study has several limitations. First, the sample size only included three schools, which may limit the generalizability of the findings due to the small sample size. Second, although teacher was included as a categorical variable to account for classroom-level differences, unmeasured instructional practices or school policies may have influenced outcomes that the model was unable to capture. Finally, defining and measuring "student engagement" is a challenge. While time logged into the modules and exam duration provide some indication of engagement, these do not account for individual differences in motivation, learning strategies, or learning that occurred from other experiences outside the scope of this study. Future research should explore more nuanced methods for capturing engagement, such as tracking specific interactions within the ITS platform, using qualitative student feedback, or using teacher feedback.

Conclusion

This study examined factors that affected high school students' performance on the ALEKS College Mathematics Placement Exam. The factors that influenced student outcomes on the ALEKS Mathematics Placement exam included the amount of time spent taking the post-test exam in May, the expectations of the classroom teacher, and the number of modules mastered. Students who spent more time taking the post-test exam outperformed students who did not. Students who completed more modules scored higher on the post-test exam than those who did not. Students whose teachers required participation were more engaged with the modules and the exams.

These results suggest that students who were motivated to complete the learning modules, and students who took their time to complete the exam, had better performance outcomes. Based on these findings, teachers are encouraged to set clear expectations for module use, monitor student progress regularly, and incorporate ALEKS module completion into the course grade to ensure accountability. Teachers should also provide guidance on effective test-taking strategies, emphasizing the importance of slowing down and reading each question carefully. Schools who supplement their current math curriculum with ALEKS, using best practices identified here, can improve students' learning and college math preparation. Higher placement exam scores can help students avoid remedial coursework, saving time and tuition as they begin their college journey.

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