An analysis of the relation between student usage and course outcomes for MyLabMath and MyLab Foundational Skills

Pearson Global Product Organization
Efficacy & Research
Impact Evaluation

Executive summary

Product descriptions

MyLab Math [1](2014-15) is an online tutorial and assessment tool for teaching and learning mathematics. It is designed to provide engaging experiences and personalized learning for each student so that all students can succeed. The homework, quizzes and tests include immediate feedback when students enter answers, which research indicates strengthens the learning process (Bangert--Drowns, Kulik, Kulik, & Morgan,1991; Hattie, 2009; Hattie & Timperley, 2007; Sadler, 1989). MyLab Math automatically tracks students' results and includes item analysis to track class-wide progress on specific learning objectives. QuizMe was also part of the MyLab Math Study Plan, which for some students provided a faster path through the course. For example, if students passed the QuizMe knowledge checks, they could skip some of the Study Plan's practice exercises.

MyLab Foundational Skills [2](2014-15) is an online mastery and competency-based resource. It is used for assessing and remediating college and career readiness in reading, writing, mathematics, study skills, and digital literacy. MyLab Foundational Skills does this by first applying a diagnostic assessment to identify students' strengths and weaknesses. By engaging in homework, quizzes and tests, students are able to master skills at their own level, working at their own pace.

The versions of MyLab Math and MyLab Foundational Skills analyzed in this study also had adaptive learning resources provided by an outside vendor, which could be activated to support personalized learning; however, as the outside vendor's usage data was not interpretable for this study, the efficacy of these adaptive features of MyLab Math and MyLab Foundational Skills was not analyzed.

Intended outcomes

MyLab Math: one of the greatest challenges that colleges in the United States face is that many students enter unprepared to complete college level mathematics courses. Most colleges have a sequence of developmental mathematics courses that start with basic arithmetic and then go on to pre-algebra, elementary algebra, and finally intermediate algebra, all of which a student must complete and pass before enrolling in a credit-bearing mathematics course. MyLab Math is designed to provide students with a positive, personalized learning experience that will help them develop a beneficial mind-set in math, so that they can achieve the prerequisite math skills that will enable them to successfully complete credit-bearing mathematics courses.

MyLab Foundational Skills: each course offers comprehensive content, including assessment, instruction, practice and post-assessment. These may be used as is, or customized to the specific objectives of a program. MyLab Foundational Skills uses diagnostic assessment to generate a personalized learning path that supports curriculum and skills mastery. The adaptive learning path allows students to learn at a level and pace that is aligned with their individual needs, with the ultimate goal of an improved learning experience and higher achievement for better overall outcomes.

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[1] When this study was carried out, MyLab Math was known as MyMathLab. For consistency, we refer to the product by its current name throughout this report.

[2] When this study was carried out, MyLab Foundational Skills was known as MyLabFoundational Skills (no space). For consistency, we refer to the product by its current name throughout this report.

Research focus and research questions

This study aimed to deepen understanding of the relation between courseware activity usage and course outcomes. Such research has the potential to provide educators and courseware developers better evidence on how to optimize implementation of courseware technologies. This technical report presents findings from an analysis of courseware usage data from these two Pearson products, MyLab Math and MyLab Foundational Skills, in two contrasting college settings (a 4-year and 2-year institution) and two different subject areas (mathematics and English language arts).

To develop this report, researchers from SRI International leveraged course outcome data collected from 2014 through 2015 from two college campuses that participated in the Adaptive Learning Market Acceleration Project (ALMAP), sponsored by the Bill & Melinda Gates Foundation.

They also gathered new Pearson data, which included metrics of courseware usage (e.g., hours per task and attempts per task) and performance (e.g., scores per task, and learning objectives attempted and mastered). These metrics were gathered for homework, test and quiz courseware activities. In the case of MyLab Math only, the QuizMe activity data was also collected. QuizMe activities are knowledge checkpoints that, if passed, permit students to skip assigned practice exercises in their Study Plans. Mastery of objectives in MyLab Math was based on aggregated data from the Study Plan, specifically both the practice and QuizMe activities. Mastery of objectives in MyLab Foundational Skills was based on aggregated data from homework, quizzes, and tests at a percentage (e.g., 70% correct or 80% correct, etc.) set by the instructor.

For both institutions and both Pearson products, this report presents descriptive statistics and inferential statistical models that used the courseware usage and performance data to predict course grades and course completion (i.e., passing a course). The models controlled for student background characteristics commonly used in education research, including gender, ethnicity, Pell status, enrollment status (full time or part time), and measures of student prior achievement or a proxy, when available. Since analyses revealed a high correlation among the courseware activity variables, analysts consulted with Pearson to select the variables of interest to include in the models reported here.

The study addressed the following research questions:

1. What were the trends in the students' use of and performance in the courseware?
2. Controlling for student demographic and prior achievement variables, is student courseware use and performance associated with course outcomes?

Key findings

The results of the present study were as follows:

Courseware usage and performance trends by institution

- During each of each of two 17-week academic periods at Arizona State University (ASU), each student spent an average total of 32 hours in the MyLab Math courseware. Most activity was spent in QuizMe, the automated quiz activity in the MyLab Math Study Plan. QuizMe checks knowledge either (1) after students engage in practice activities, or (2) before students engage in practice, to document competency and permit skipping redundant practice activities. SRI did not have any usage data from Study Plan practice activities, which are distinct from homework activities. Nearly two-thirds of ASU students did not attempt homework activities in MyLab Math. On average, ASU students made about 80 attempts over the full course in QuizMe. Across the three primary activity types for which SRI had usage and performance data for ASU students — quizzes, QuizMe quizzes, and tests — the average performance score was 69%. On average, students attempted 52 learning objectives and mastered 51 of them, based on data from the Study Plan's QuizMe quizzes.

- Over each of Rio Salado's three 13-week academic periods, each student spent an average total of 18.8 hours in MyLab Foundational Skills courseware. On average, Rio Salado students made about 103.6 attempts at homework assignments over the full course. On average, Rio Salado students made about 32.89 test attempts per academic term. The average Rio Salado student's score across the three primary activity types — homework, quizzes, and tests — was 91%. On average, students attempted 229 learning objectives, but mastered only about 124 of them, based on data aggregated across homework, quizzes, and tests.

Predicting course outcomes from usage data

Controlling for the selected student background characteristics, several courseware usage and performance variables significantly predicted the two course outcomes at each institution: course grades and completion. In exploring the usage data, however, SRI discovered many high correlations and multicollinearity issues that prevented full use of all activity types and usage metrics (e.g., hours and attempts) in our predictive models (for details, see Appendix D). For ASU, we were unable to include both hours and attempts because of multicollinearity issues. In consultation with Pearson, we chose to use attempts as our preferred usage variable. Also, in the case of ASU, we included all activity types except homework because too few students used those activities in the courseware. For Rio Salado, the activity types were so highly correlated that we were able to include only one activity type. In consultation with Pearson, we chose to use homework as our preferred activity variable.

MyLab Math at ASU:

- **Course grades:** the model showed that three usage and performance trends — increased attempts on quizzes and tests, increased average scores on quizzes and tests, and increased learning objectives mastered — were associated with significantly higher course grades, controlling for the selected student-level background characteristics. However, having a greater number of MyLab Math QuizMe attempts and achieving better scores in QuizMe quizzes in the Study Plan were associated with statistically significant lower course grades, when controlling for student-level background characteristics. (See Table 1 for a visual summary.)
- **Course completion (e.g., passing the course):** the models showed that three usage and performance trends — increased attempts in quizzes and tests, increased average scores on quizzes and tests, and increased learning objectives mastered — were associated with increased likelihood of students completing a course, when controlling for the selected student-level background characteristics. In addition, female students who made more test attempts, scored higher on the tests, or mastered more objectives were more likely to pass their courses than males. Male students who made more quiz attempts were more likely to pass their courses than females. Finally, one negative association was found between performance in the courseware and course completion: increases in average QuizMe scores were negatively associated with completing the course. (See Table 2 for a visual summary.)

Table 1: *relation of MyLab Math activity attempts, scores, and learning objectives mastered to ASU course grades*

Student usage/performance variable	**Type of assignment**		
	Quiz	**QuizMe**	**Test**
Number of attempts	↑	↓	↑
Score	↑	↓	↑
Number of objectives mastered	↑		

↑ Positive association: higher values for factor linked significantly with higher course grades.
↓ Negative association: higher values for factor linked significantly with lower course grades.
⊘ No significant association: factor unrelated to course grade.

Table 2: *relation of MyLab Math activity attempts, scores, and learning objectives mastered to ASU Course completion (passing)*

Student usage/performance variable	**Type of assignment**		
	Quiz	**Quiz Me**	**Test**
Number of attempts	↑	⊘	↑
Score	↑	↓	↑
Number of objectives mastered	↑		

↑ Positive association: higher values for factor linked significantly with higher probability of passing the course.
↓ Negative association: higher values for factor linked significantly with lower probability of passing the course.
⊘ No significant association: factor unrelated to probability of passing course.

MyLab Foundational Skills at Rio Salado:

- **Course grades:** both a higher number of homework attempts and a higher number of learning objectives mastered, based on aggregate data from homework, quizzes and tests, were associated with statistically significant higher course grades, when controlling for the selected student-level background characteristics. There was a negative association between attempting learning objectives and course grades (Table 3).
- **Course completion:** the model results with course completion as the outcome variable mirror those for course grades. Making more Homework attempts and mastering more learning objectives within the courseware were associated with a higher likelihood of completing courses, after controlling for the

selected student-level background characteristics. However, we also found that making more attempts to master learning objectives was associated with a lower likelihood of completing the course (Table 4).

Table 3: *relation of MyLab Foundational Skills homework time spent, attempts, scores, and learning objectives attempted/mastered to Rio Salado course grades*

Student usage/performance variable	**Type of assignment**
	Homework
Time spent	⊘
Number of attempts	↑
Score	⊘
Number of objectives attempted	↓
Number of objectives mastered	↑

↑ Positive association: higher values for factor linked significantly with higher course grades.
↓ Negative association: higher values for factor linked significantly with lower course grades.
⊘ No significant association: factor unrelated to course grade.

Table 4: *relation of MyLab Foundational Skills homework time spent, attempts, scores, and learning Objectives attempted/mastered to Rio Salado course completion (passing)*

Student usage/performance variable	**Type of assignment**
	Homework
Time spent	🛇
Number of attempts	⬆
Score	🛇
Number of objectives attempted	⬇
Number of objectives mastered	⬆

⬆ Positive association: higher values for factor linked significantly with higher probability of passing the course.
⬇ Negative association: higher values for factor linked significantly with lower probability of passing the course.
🛇 No significant association: factor unrelated to probability of passing course.

Recommendations

We provide separate recommendations for each courseware product.

Consistent with past studies of MyLab Math, the findings suggest that quiz and test scores in the courseware are related to higher grades in a college-level algebra class and a higher probability of passing the course. The study also found that most ASU students were not engaged with the courseware's homework assignments, but instead using the Study Plan tool that features practice and QuizMe quizzes. The data indicates that students, on average, achieved mastery of nearly all the courseware learning objectives based on data from QuizMe quizzes, which was a trend associated with positive course grades and passing the course.

The results show negative relations for both QuizMe attempts and QuizMe scores with course grades. Without more detailed usage data focused on behaviors associated with productive persistence, this outcome cannot be interpreted definitively. However, we speculate that this outcome likely stems from student efforts to "game" the Pearson courseware and not engage in productively persistent learning activity. For example, a high average number of QuizMe attempts and low course outcomes is consistent with students who skip practice activities, and instead repeatedly take guesses at QuizMe quizzes until they achieve a passing score. This behavior drives up the number of QuizMe attempts. However, students have not necessarily learned the material, which shows in lower course grades. On the other hand, obtaining higher QuizMe scores and low course outcomes may stem from two types of behavior: one consistent with gaming the system and one consistent with productive persistence. Students attempting to game the system may pursue a limited number of learning objectives and achieve high average scores on those few QuizMe quizzes, but have not covered enough material to do well in the course. However, more persistent students may attempt a higher number of learning objectives and achieve a lower average QuizMe score, but have covered sufficient material to do well in the course.

With respect to MyLab Foundational Skills, the findings suggest that more homework practice in the courseware and more courseware learning objectives mastered are both associated with higher grades in two developmental writing courses and a higher probability of passing these courses. However, the study also found that Rio Salado students attempted nearly twice as many learning objectives as they mastered. Without more data on how the courseware was implemented in these online classes, we cannot interpret these findings definitively.

Next steps

There were several limitations to this study. In the models, we attempted to control for any bias that could be introduced by students' background characteristics and prior skill level by including measures of those characteristics common to educational research (e.g., gender, ethnicity, Pell grant status, full- or part-time enrollment status) and incoming skill level. Despite these controls, these measures probably did not capture all the possible confounding factors that might influence use and course outcomes, such as student motivation, family support, and prior learning experiences with technology. As a result, while results of these analyses can help indicate whether a relation between use and learning outcomes exists, they cannot be used to establish with certainty whether product use caused better student learning outcomes. There are multiple plausible explanations for any of the reported associations. Thus, the findings associated with these analyses should be treated as exploratory and positive associations as promising, but not definitive evidence of a causal connection between product use and improved learning and skill development.

In addition, the samples at each campus in this study were smaller than those in the original ALMAP study because, for these analyses, researchers needed to match students in the ALMAP sample with their Pearson courseware usage data. For a variety of reasons explained in detail in the report, we could not match data in many cases in the two data sets. Thus, the original ASU sample of 2,475 was reduced to an analytical sample of 1,570, and the original Rio Salado sample of 964 was reduced to 327 students. The resulting student samples varied demographically across the two institutions. ASU students were evenly split between men (46%) and women (54%), were mostly White and Asian (61%), were full-time students (95%), and less than a third relied on Pell grant financial aid. In contrast, Rio Salado students were mostly women (63%), were more representative of diverse races/ethnicities (48% White or Asian; 43% other populations), were enrolled mostly part time (73%), and more than half relied on federal Pell grant assistance.

Other limitations were that not all instructors participated in the ALMAP surveys, and those surveys did not focus specifically on elements of the MyLab Pearson products. However, some of those instructor survey items did shed light on specific courseware implementation challenges. For example, ASU instructors noted that students "rushed through" the courseware content and focused on "getting the points", rather than deeply learning. The Rio Salado instructors said that they had difficulty importing grades from MyLab Foundational Skills into their online grading system, inserting customized writing assignments into the courseware, and providing feedback to students. They also described their students as not being "savvy" to the system and failing to find required writing assignments in it. All faculty respondents at both campuses noted that they could track individual and class progress using the two courseware products.

Overall, the findings indicate that future studies exploring MyLab courseware usage data would be enhanced by collection of class implementation details about (1) the specific MyLab courseware activities that instructors assign, (2) their methods of integrating the courseware scores into class grading systems, and (3) the assumptions that both students and instructors make about how to use the MyLab courseware to support learning. Of particular interest is building an understanding of how instructors guide students to engage in the courseware activities, specifically homework, quizzes, and tests, and, in the case of MyLab Math, understanding the trade-offs of replacing engagement in these three activities with a Study Plan that emphasizes practice activities and QuizMe quizzes. Future studies also should include usage data from all features of the system, including practice activities in the Study Plan.

This study provides some further information on how to control for variations in students' baseline knowledge. In a past internal MyLab Math study (Pearson Education, 2016), analysts used prior term grades as a baseline knowledge measure with a subset of students. Using this as the prior achievement variable, Pearson analysts found that the number of courseware learning objectives mastered failed to predict passing a course. However, when the current study used college entrance examination scores as a baseline knowledge measure (e.g., as part of the ALMAP study), it found that the number of learning objectives mastered in MyLab Math courseware not only predicted passing the course, but also predicted higher course grades. These contrasting results raise questions about the analyses that use prior GPA as opposed to standardized test scores as proxies for prior achievement. A third option for establishing prior knowledge used in the ALMAP study was found to be most precise: using an assessment of prior knowledge on the academic content relevant to a particular course. The study also provides some support for the theory advanced in the prior internal MyLab Math report that homework and quizzes can help students master the course material. In the current study of MyLab Math, higher attempts (e.g., more practice) with quiz items (and test items) significantly predicted higher course grades and passing the course.

For MyLab Foundational Skills, this study indicated a negative relation between learning objectives attempted, and both course completion and grades. Further, there was the wide gap between the number of learning objectives attempted by the Rio students and those they mastered within the courseware. We also should note that Rio students were receiving Study Plan guidance from the outside vendor's adaptive algorithm, but how and when they were using those recommendations was not interpretable from the algorithm data available for this analysis. Without more algorithm usage data and classroom implementation data — such as how instructors incorporated courseware scores toward course grades, or how students were responding to recommendations to pursue specific learning objectives — it is difficult to interpret these findings. It is unclear in the case of MyLab Foundational Skills whether students were exploring extra learning objectives out of curiosity or because they failed to understand how to navigate through the courseware and how to respond to the outside vendor's adaptive algorithm recommendations.

One high-level take-away from this study is that practicing with content until one gets individual homework problems, quiz items, and test items correct appears to lead to positive course outcomes. The study also raises questions about the value of alternative uses of the courseware, such as attempting a larger number of learning objectives than one intends to master (in the case of Rio Salado) or relying on the Study Plan's QuizMe quizzes without engaging in practice activities (in the case of ASU). These alternative practices did not appear to yield positive impacts on course performance. However, we cannot say for certain whether either of these conclusions are accurate without usage data from the Study Plan's practice activities and more information about how, and whether, faculty members integrated the courseware scores for learning objectives mastered into their course grades. Also, the study could not determine to what extent these alternative practices occurred as students responded to recommendations from an outside vendor's adaptive algorithms, as the vendor's usage data was insufficient for interpretation.

Introduction

To support student success, U.S. institutions of higher education are increasingly using courseware technologies to help students study. Such technologies include electronic textbooks that feature automatically graded homework assignments, quizzes, and practice tests. Designers of interactive electronic textbooks intend to engage students in these activities to help them achieve content mastery. However, initial research indicates that both students and faculty members engage in different degrees of courseware usage and different methods of integrating courseware scores into class gradebooks, which leads to different impacts on student course outcomes.

Understanding the relationship between courseware activity usage and course outcomes has the potential to provide educators and courseware developers better evidence on how to optimize implementation of courseware technologies. However, few public reports have drawn on the expanding data trove from students who are using these courseware products at college campuses throughout the United States. To address this research gap, this technical report offers findings from an analysis of courseware usage data from two different Pearson products: MyLab Math and MyLab Foundational Skills. This report presents results from statistical models that used courseware usage and performance data to predict course grades and course completion in two institutions of higher education.

To develop this report, researchers from SRI International leveraged course outcome data collected from 2014 through 2015 from two college campuses that participated in the Adaptive Learning Market Acceleration Project (ALMAP), sponsored by the Bill & Melinda Gates Foundation. The ALMAP study focused on adaptive learning courseware — a specific kind of online product that uses computer algorithms to parse learning analytic data so as to guide students as they study. The ALMAP study aggregated findings from adaptive courseware evaluations conducted by 14 higher education institutions. It provided an initial review of the relative efficacy of nine adaptive courseware products as they were integrated into 23 developmental and general education courses over two to three academic terms. ALMAP researchers gathered quasi-experimental evidence on course outcomes, cost data, and both instructors' and students' experiences of the courseware (Yarnall, Means, and Wetzel, 2017). However, one notable gap in the original ALMAP study was the lack of access to, and analysis of, the courseware-generated data on student product usage and performance.

In 2016, to deepen understanding of how its own products were used in the ALMAP courses, Pearson Education hired SRI International, the research institute that conducted the original ALMAP study, to examine how student usage of and performance in MyLab Math and MyLab Foundational Skills related to course outcomes.

Overview of foundational research

This section summarizes the education research that informed the design of each of the two products discussed in this report.

MyLab Foundational Skills is an instructional program based on providing students with a learner-centered environment that builds and supports developmental progression through the course. The version of MyLab Foundational Skills studied in this report featured personalized and adaptive learning paths provided through the services of an outside vendor.

The design of MyLab Foundational Skills is aligned with several areas of education research in the learning sciences — diverse, transdisciplinary fields that seek to understand how humans learn. Using insights distilled from the learning sciences, a number of learning design principles have been developed that guide the creation of our products. MyLab Foundational Skills demonstrates a number of these learning design principles, as follows.

Adaptivity

Successful instruction must help students quickly establish a foundation of knowledge and skills, as well as provide opportunities and support for developing more advanced mastery levels. Adaptive learning technologies, such as MyLab Foundational Skills, are one promising approach that research has explored to address this. As students gain proficiency, the learning opportunities can transition from being highly scaffolded and knowledge focused, to more open ended and focused on conceptual understanding and adaptation of knowledge, following research on the "expertise-reversal effect" (Kalyuga, Ayres, Chandler, & Sweller, 2003). The adaptive functionality of MyLab Foundational Skills provides specific and immediate feedback, so students can build confidence and proficiency in their skills. Subsequent items are then selected based on students' performances on previous items.

Scaffolding and fading

Research has found that novices learn and process information in fundamentally different ways than those with more background knowledge (Chi, Feltovich, & Glaser, 1981). Specifically, novices require more support because they do not have a body of relevant knowledge and strategies to draw on to help them solve new problems or learn new information. Thus, it is critically important to *scaffold*, or support, novice learners in a variety of ways.

In MyLab Foundational Skills, there are a variety of learner support tools, including specific, clear, concise, and timely feedback that is provided in association with practice activities. These tools help to scaffold learning and improve the likelihood of increased achievement.

Learner feedback

The role of feedback in promoting successful learning outcomes is well documented (see Hattie & Timperley, 2007). When students receive feedback indicating that they have made an error, there is an opportunity to provide supplemental information that can help them address whatever issue is keeping them from answering correctly (whether insufficient background knowledge, a problem-solving error, or a particular misconception).

In MyLab Foundational Skills, when students give wrong answers, they receive feedback with help on how to correct errors. In addition, resource tools, such as *Ask My Instructor, Help Me Answer This and View an Example* can further help students with the assessments.

Memory strategies

A number of research-supported strategies for optimizing the presentation of to-be-learned information have been developed. These draw on bodies of research on memory and focus, in particular, on improving *retrieval* (i.e., how well information can be recalled when needed). A very robust finding is that increased repetition can indeed help students learn compared with isolated presentations of information, as described by research on the benefits of "retrieval practice" (see Karpicke & Roediger, 2010). This research demonstrates that, generally speaking, learners benefit from more practice. In MyLab Foundational Skills assessments, items are given in a manner that supports long-term retention through timely repetition, thereby aligning with research on the benefits of retrieval practice.

Teacher feedback

In MyLab Foundational Skills, instructors can see a student's basic performance from overview reports (e.g., number of items correct/incorrect, attempted). Instructors can also see details on specific learning objectives with a gradebook that allows for tracking the student's performance as it corresponds to the learning outcomes for the course. *Item analysis* allows instructors to track and adapt individual tasks and specific learning objectives within the course, as and when needed.

MyLab Math is aligned with the insights gained from more than 30 years of research on intelligent tutoring systems (e.g., Anderson, Corbett, Koedinger, & Pelletier, 1995; Ohlsson, 1986). In particular, MyLab Math helps students turn the knowledge they gain in class and through studying their textbook into procedural fluency by offering extensive and well-supported practice (Anderson & Schunn, 2000). This process of developing expertise is supported by offering immediate feedback, providing different kinds of support (i.e., worked examples, hints), focusing students' attention on critical elements, and managing the load on students' working memory (Sweller & Cooper, 1985). All these strategies and features are intended to enable students to succeed in math, often for the first time.

MyLab Math contextualizes all help functionality for developmental math students to help them succeed at solving the problem at hand. Developmental math students serve to benefit from establishing a pattern of success in mathematics. The contextualized learning aids in MyLab Math help guide students to begin a positive journey through the material with the aim of leading to greater success.

Mindset

In educational psychology research, a number of research areas deal with understanding the motivations, beliefs and attitudes that may prevent students from achieving their potential, and detail strategies for helping students adjust those non-cognitive factors. Specifically, three areas of importance are dealing with anxiety (Maloney & Beilock, 2012), personal relevance (Hulleman, Godes, Hendricks, & Harackiewicz, 2010), and growth mindset (Dweck, 1996). These are areas where MyLab Math aims to help students.

Mindset is a key outcome validated by instructors as being important to them and their students. People tend to gravitate toward one of two mindsets when it comes to learning in a given domain. People with a *fixed* or (*entity*) mindset believe that ability is innate (Dweck, 1996). For example, someone who believes that they are just not good at math and never will be has a fixed mindset. By contrast, people with a *growth* (or *incremental*) mindset believe that ability is developed through practice and effort. Research has shown that adopting a growth mindset has a number of positive influences on learning. Students with a growth mindset are more likely to adopt more learning oriented goals, persist longer (Diener & Dweck, 1978), use better learning strategies, and ultimately achieve better grades (Yeager & Dweck, 2012).

Scaffolding with worked examples

MyLab Math offers a variety of learner support tools to help students struggling with assessment items. These support tools include hints, videos, animations, and e-text. Further, students can ask for help and get step-by-step support in solving a math problem. These support tools are aligned with research on best practices for scaffolding in technology-enhanced learning environments (Sharma & Hannafin, 2007).

Feedback

MyLab Math enables students to check frequently on their understanding and receive immediate feedback, which is one of the most effective means for building long-term retention and increasing student confidence and motivation (Hattie, 2009, 2012). Feedback provided in association with practice activities in MyLab Math, is specific, clear, concise and timely. Instructors see basic student performance (e.g., number of items correct/incorrect, attempted) on assignments, and students can see detailed performance on specific learning objectives.

Cognitive load

In cognitive psychology, *cognitive load* refers to the total amount of mental effort being used in working memory (Miller, 1956). This includes extraneous cognitive load — the mental effort spent on distracting elements that are not relevant to the learning. Research shows that reducing extraneous cognitive load for students when they are reading or studying improves the effectiveness of learning (Sweller, 1988). Put simply, when distractions are removed, learning is more likely to occur. In MyLab Math, extraneous cognitive load is kept low through the following approaches: topics and subtopics are organized coherently into manageable chunks, assessments are presented in a clean area, and the e-text is accessible and easy to read.

Adaptivity

Research has identified two types of adaptivity in learning technologies. One type relates to adaptive responses to students (i.e., adaptive feedback). Similar to the research described about feedback, adaptive systems that provide timely feedback to students as they engage with the learning technology have been shown to be as effective as human tutors (VanLehn, 2011). The other mode of adaptivity relates to adapting a learning sequence based on an understanding of a student's current proficiency. One way this can be done is by estimating each student's mastery understanding of skills and concepts, based on his or her performance, and ensuring that students receive enough practice to achieve fluency with the content. This "knowledge tracing" has been used to great effect (Corbett & Anderson, 1995). MyLab Math uses the latest advances in adaptive learning technology, offering two options: the adaptive companion Study Plan and personalized homework. Instructors have the flexibility to incorporate the style and approach of adaptive learning that best suit their course structure and students' needs.

Additional context on QuizMe

QuizMe is part of the Study Plan in MyLab Math, which for some students provides a faster path through the course. For example, if a student passes the QuizMe quiz right away, she does not have to complete the Study Plan practice.

Description of courseware products

MyLab Math (2014-15) is an online tutorial and assessment tool for teaching and learning mathematics. It is designed to provide engaging experiences and personalized learning for each student, so that all students can succeed. The homework, quizzes, and tests include immediate feedback when students enter answers, which research indicates strengthens the learning process (Bangert--Drowns, Kulik, Kulik, & Morgan,1991; Hattie, 2009; Hattie & Timperley, 2007; Sadler, 1989). MyLab Math automatically tracks students' results and includes item analysis to track class-wide progress on specific learning objectives. QuizMe also was part of the MyLab Math Study Plan, which for some students provided a faster path through the course. For example, if students passed the QuizMe knowledge checks right away, they could skip some of the Study Plan's practice exercises.

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The versions of MyLab Math and MyLab Foundational Skills analyzed in this study also had adaptive learning resources provided by an outside vendor, which were intended to support personalized learning. However, as the outside vendor's usage data were not interpretable for this study, the efficacy of these adaptive features of MyLab Math and MyLab Foundational Skills were not analyzed.

Intended outcomes

MyLab Math: one of the greatest challenges that colleges in the United States face is that many students enter unprepared to complete college level mathematics courses. Most colleges have a sequence of developmental mathematics courses that start with basic arithmetic and then go on to pre-algebra, elementary algebra, and finally intermediate algebra, all of which a student must complete and pass before enrolling in a credit-bearing mathematics course. MyLab Math is designed to provide students with a positive, personalized learning experience that will help them develop a beneficial mindset in math, so that they can achieve the prerequisite math skills that will enable them to successfully complete credit-bearing mathematics courses.

MyLab Foundational Skills: each course offers comprehensive content including assessment, instruction, practice, and post-assessment. These may be used as is, or customized to the specific objectives of a program. MyLab Foundational Skills uses diagnostic assessment to generate a personalized learning path that supports curriculum and skills mastery. The adaptive learning path allows students to learn at a level and pace that is aligned with their individual needs, with the ultimate goal of an improved learning experience and higher achievement for better overall outcomes.

The present study

For this report, SRI used the past ALMAP course outcome data collected from Arizona State University (ASU) and Rio Salado College. Over the two to three academic terms constituting the ALMAP study at each campus from 2014-2015, ASU integrated Pearson's MyLab Math into an introductory algebra course offered at three campuses, and Rio Salado College implemented MyLab Foundational Skills in a set of online developmental English classes. For the current follow-up study, Pearson provided usage data for these courseware implementations at these institutions, and each of the institutions provided Pearson and SRI with student identifiers to connect the ALMAP study data to the Pearson usage data. Pearson's usage data captured how students used specific activities in the courseware products, including homework, quizzes, tests, and one other specialized activity in MyLab Math, called QuizMe. Pearson usage data also examined how many courseware learning objectives students attempted and mastered. Although both MyLab Math and MyLab Foundational Skills included adaptive learning features through the outside vendor's learning system, the outside vendor's data set on the use of those adaptive features was not sufficient to support analysis.

In addition to presenting statistical predictive models of how courseware usage relates to course outcomes, this report describes both usage trends — time logged per courseware activity and number of practice attempts in courseware activities — and performance metrics — achievement scores in those activities and the number of learning objectives attempted and mastered.

The predictive statistical models were developed based on courseware usage in two contrasting college settings (4-year ASU and 2-year Rio Salado) and in two different subject areas (mathematics and English language arts). These models were used to explore the extent to which MyLab Math / MyLab Foundational Skills usage and performance data could be used to predict students' course outcomes, specifically course completion and course grades. The models controlled for student background characteristics commonly used in education research, including gender, ethnicity, Pell status, enrollment status (full time or part time), and measures of student prior achievement or a proxy, when available.

The study addressed the following research questions:

1. What were the trends in the students' use of and performance in the courseware?
2. Controlling for student demographic and prior achievement variables, is student courseware use and performance associated with course outcomes?

Method

In this section, we describe the data transfer and linking procedures, the Pearson data and its use in the analytical models, and the analytical sample.

DUA and data transfer procedures

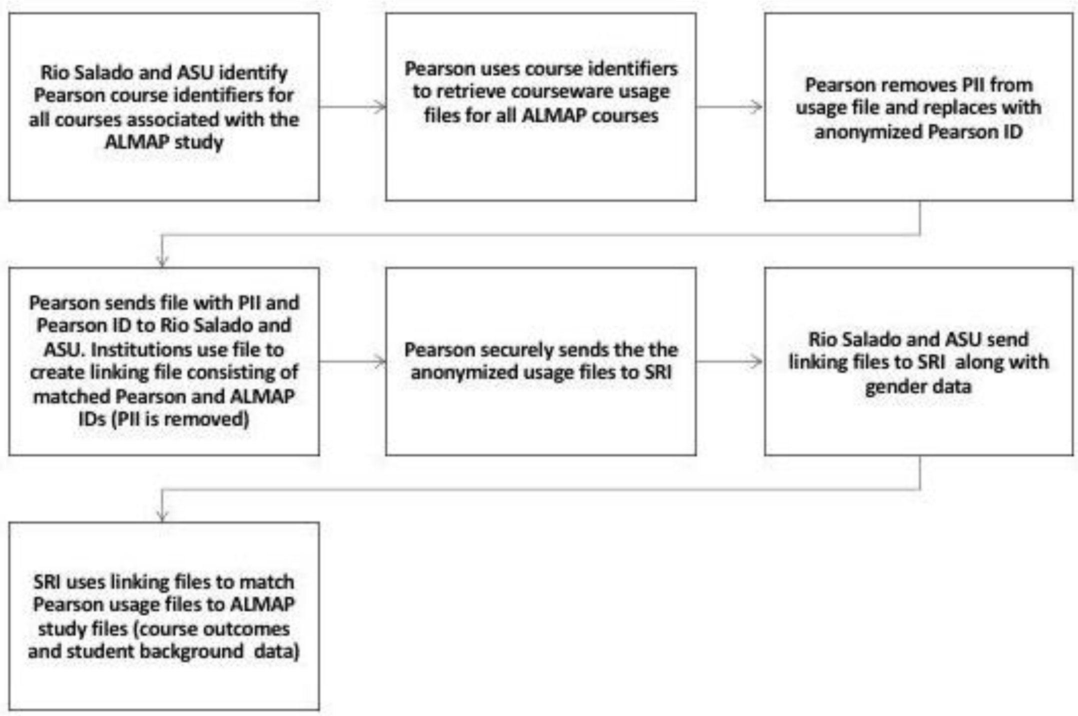
To share data among the various entities, Data Use Agreements (DUAs) were established between Pearson Education and ASU and Rio Salado, and between Pearson and SRI. These DUAs set the scope and terms by which courseware and other data were to be shared. The DUAs also helped ensure that the data would be shared in a manner that protected students' personally identifiable information and complied with terms of the original ALMAP study's human subjects research protection agreements with each education institution. All ASU, Rio Salado, and Pearson data files were transmitted to SRI via a secure, password-protected online transfer system. Files were locally encrypted before transfer and decrypted by SRI only after being stored in a limited-access data server.

Data linking procedures

To conduct the study, we needed to link the existing student demographic and course outcome data file prepared under the ALMAP study, with the courseware usage data archived by Pearson. The ALMAP data in SRI possession were anonymized (ALMAP study ID), as were the courseware data Pearson provided to SRI (Pearson study ID). To facilitate the linking process, Pearson shared with each institution the anonymized Pearson study ID for each student and the personally identifiable information it collected on each student (email addresses) when students enrolled in the courseware. The institutions then used that information to create a "linking" file that mapped the ALMAP study IDs to the Pearson Study IDs and then shared this linking file with SRI. In addition, to explore possible differences in courseware usage and outcomes by gender, SRI obtained additional gender data from each campus to include in the analyses. SRI then used the linking file to merge the Pearson courseware usage files and ALMAP student data files that consisted of student demographics, a prior achievement score, and course outcomes (see Figure 1).

Data managers at ASU and Rio Salado retrieved the original Pearson course identification numbers associated with the courses in the original ALMAP study. Ultimately, the data managers retrieved course identification numbers for 19 English courses at Rio Salado and 72 mathematics courses at ASU. These course numbers were listed in the DUA, and aligned with courses offered at ASU during the winter and fall terms of 2014, and three terms at Rio Salado (January-August 2014, August 2014-March 2015, and January-August 2015).

Figure 1: *procedures for sharing student-level data*



Pearson analysts used these course identification numbers to retrieve the relevant student courseware usage data (such as “attempts”) and student performance data (such as “mastery of learning objectives”) for each type of courseware activity in the study, including homework, quizzes, tests, and QuizMe (in MyLab Math only).

Next, each institution provided SRI with the linking file that connected the original anonymized ALMAP student identifiers with anonymized student identifiers that Pearson had inserted into the courseware usage files to protect students’ personally identifiable information for this study. ASU and Rio Salado also provided SRI with additional data on student gender that had not been collected in the original ALMAP study.

The Pearson usage data

For the study described in this report, SRI analysts worked with five main types of Pearson activity data: homework, tests, quizzes, learning objectives, and, for MyLab Math only, QuizMe. For the activity types of homework, tests, quizzes, and QuizMe, there were three variables of interest: total hours in the activity, total attempts (which represents when a student successfully answers the problem or item, or exhausts the maximum number of permitted tries for completing each homework problem, Quiz item, or test item) (Anderson, J., Kukartsev, G., & Rho, Y. J., 2015) and the standardized average grade (percentage correct plus extra credit) within that activity. Two additional variables of interest related to learning objectives: number of learning objectives attempted and number of learning objectives mastered.

Table 1 shows the data elements used in the analyses for this report. The table displays the source of the data and its purpose in the descriptive analyses and linear inferential statistical modeling.

Table 1: *data elements reviewed in the data audit procedure*

Data element	Data source	Analytic purpose
Student gender	Institutions of higher education	Sample descriptive

		Covariate control
Student Pell grant status (socioeconomic status indicator)	Institutions of higher education (access during ALMAP study)	Sample descriptive Covariate control
Student race / ethnicity	Institutions of higher education (access during ALMAP study)	Sample descriptive Covariate control
Student full-time vs. part-time enrollment status	Institutions of higher education (access during ALMAP study)	Sample descriptive Covariate control
Prior achievement	Institutions of higher education (access during ALMAP study) ASU: ALEKS Pretest Rio Salado: Accuplacer Essay	Sample descriptive Covariate control
Homework: • time on task (hours) • attempts • scores (standardized)	Pearson courseware usage data	Activity descriptive Predictor variable
Quizzes: • time on task (hours) • attempts • scores	Pearson courseware usage data	Activity descriptive Predictor variable
QuizMe (ASU MyLab Math only): • time on task (hours) • attempts • scores	Pearson courseware usage data	Activity descriptive Predictor variable
Tests: • time on task (hours) • attempts • scores	Pearson courseware usage data	Activity descriptive Predictor variable
Learning objectives: • attempted • mastered	Pearson courseware usage data	Activity descriptive Predictor variable
Course grades	Institutions of higher education (during ALMAP study)	Outcomes descriptive Outcome variable
Course completion	Institutions of higher education (during ALMAP study)	Outcomes descriptive Outcome variable

Analytical Samples

Table 2 provides an overview of the total sample sizes available in the different data sets that SRI analysts merged for analysis.

To be included in the analytic sample for this study, a student record from the original ALMAP study had to meet several requirements:

1. The students had to be unique, meaning we only included data from a single term. If a student appeared in more than one term, we included the record from the student's first term and discarded records associated with the additional terms.
2. The records had to have a complete set of Pearson usage variables (no missing data), which required every student to have an outside vendor's adaptive learning data to ensure comparability of learning condition for all students.
3. A complete set of demographic, prior achievement (i.e., pretest proxy data), and course outcome variables had to be available (no missing data).

Table 2: *sample sizes of ALMAP data, Pearson usage data, and final merged analytic data set for the ALMAP extension study*

Data corpus	**ASU / MyLab Math** ***N*** **of students**	**Rio Salado / MyLab Foundational Skills** ***N*** **of students**
Unique students from ALMAP data	2,475	964
Unique ALMAP students identified in Pearson use data	2,107	352
Matched Pearson-ALMAP records with complete set of Pearson use variables and student-level characteristics and outcomes	1,570	342
Final analytic sample	1,570	327

Note: Factors associated with reductions in the available sample for analyses relative to the unique students in the ALMAP sample varied by institution. For Rio Salado, the reduction was associated with students whose data could not be located in the Pearson database and students who reenrolled in the same course over multiple terms (data was included only from their first enrollment). In the case of ASU, SRI analysts discovered that the outside vendor's product probably was not used in the first term, so students enrolled in courses during this term were dropped from the analytical sample to maintain consistency of the learning condition across the ASU sample. In the original ALMAP study, ASU had 11 instructors and 2,144 students, and Rio Salado had 14 instructors and 456 students. In the current follow-on study, ASU had 11 instructors and 1,570 students, and Rio Salado had 8 instructors and 327 students.

The full details on data available per data variable appear in Appendix A, and the details on data auditing, cleaning and merging appear in Appendix B.

Students at ASU and Rio Salado included in the analytical samples differed in background characteristics (Table 3).

Table 3. *Characteristics of the ASU and Rio Salado student samples*

Characteristic	**ASU (*N* = 1,570)**	**Rio Salado (*N* = 327)**
Gender		
Male	46.43%	36.70%
Female	53.57%	63.00%

Race/ethnicity		
ORP	60.83%	47.70%
URP	37.90%	43.43%
Enrollment status		
Part-time	5.48%	73.39%
Full-time	94.52%	26.61%
Pell status		
Pell grant recipient	31.78%	58.41%

Note: for gender and ethnicity, percentages do not add up to 100% as some students did not reply to all questions.

ORP = Overrepresented populations: White and Asian; URP = Underrepresented populations: non-White or non-Asian

Results

The analysts examined trends in courseware usage and performance and developed models to explore how courseware usage and performance predicted course grades and course completion. The results are presented in two sections. First, we review the courseware usage and performance for each courseware product. Second, we present the results of analyses of the relation of courseware usage and performance to course grades and course completion.

Analysis of courseware usage and performance

This section provides a comparative view of courseware usage and performance at ASU and Rio Salado. Courseware usage was reflected in time logged in the courseware across all activities (e.g., homework, tests, quizzes, QuizMe) and learning objectives attempted. Courseware performance was reflected in mean achievement scores across each of the courseware activities and learning objectives mastered.

To put these courseware usage and performance data in context, it helps to remember that each institution used a different Pearson courseware product: ASU used MyLab Math, and Rio Salado used MyLab Foundational Skills. It also helps to understand the instructional settings at each institution. At ASU, a 4-year comprehensive university, instructors used MyLab Math for two 17-week academic terms to support a freshman mathematics course that met face-to-face three times a week for 50 minutes at the Tempe campus, and two times a week for 75 minutes at one other system campus (West). At Rio Salado, a 2-year college that offers most of its classes online, instructors used MyLab Foundational Skills for three 13-week academic terms to support learning in two different developmental writing courses. Students may access the online courses at any time of the week.

ASU students spent most of their time in the courseware logged into QuizMe, the automated quiz activity in MyLab Math managed by the instructor (Table 4). Across the ASU's students' scores on the three primary activity types — quizzes, QuizMe and tests — the average performance was 69%. On average, students attempted 52 learning objectives, and mastered 51 of them.

Table 4: *MyLab Math usage and courseware performance at ASU*

Usage metric	Mean	(Standard deviation)
	(*N* = 1,570)	
Time on task (hours)		
Homework[a]	.21	(0.65)
Quiz	10.89	(7.37)
QuizMe	17.86	(9.68)
Test	3.09	(1.04)
Total activity hours across all activity types per term	32.04	(14.24)
Mean activity hours per term week[b]	1.88	(.84)
Practice attempts		
Homework[a]	.49	(0.71)
Quiz	13.25	(9.89)
QuizMe	80.22	(32.13)
Test	4.46	(0.79)
Scores[c]		
Homework[a]	23.56	(36.67)
Quiz	67.3	(16.27)
QuizMe	73.7	(8.79)
Test	66.4	(16.11)
Learning objectives		
Attempted	51.84	(12.04)
Mastered	50.50	(12.70)

[a]For homework, the ASU sample was only *N* = 582 because approximately two-thirds of ASU students did not attempt any homework activities.
[b] Computed by dividing total time spent in the activities for the term by the number of weeks in ASU's academic term (17 weeks).
[c] Nonstandardized scores ranged from 0–100 percent.

Rio Salado students spent most of the time in the MyLab Foundational Skills courseware logged in to homework assignments (Table 5). The average Rio Salado student's score across the three primary activity types — Homework, Quizzes, and Tests — was 91%. On average, students attempted 229 learning objectives, and mastered about 124 of them.

Table 5: *MyLab Foundational Skills usage and courseware performance at Rio Salado*

Usage metric	Mean	(Standard deviation)
	(*N* = 327)	
Time on task (hours)		
Homework	11.03	(0.65)
Quiz	3.82	(4.79)

Test	3.95	(3.34)
Total activity hours across all activity types per term	18.80	(18.23)
Mean activity hours per term week[a]	1.44	(1.40)
Practice attempts		
Homework	103.64	(38.31)
Quiz	19.69	(7.32)
Test	32.89	(12.97)
Scores[b]		
Homework	92.9	(6.02)
Quiz	98.15	(4.60)
Test	83.5	(9.04)
Learning objectives		
Attempted	228.58	(85.13)
Mastered	123.81	(69.31)

[a] Computed by dividing total time spent in the activities for the term by the number of weeks in Rio Salado's academic term (13 weeks).
[b] Nonstandardized scores ranged from 0 to 100 percent.

Predicting course outcomes based on courseware usage and performance

Described here are the results of an examination of the relationship between courseware usage and performance, and course outcomes — course grade and completion. SRI analysts developed a series of regression models to investigate this question, estimating the relations for multiple use and performance variables in the same model. All models controlled for student background characteristics and prior achievement scores.

SRI analysts first examined the relationship among Pearson courseware usage variables to assess possible issues of high correlations among different predictors, or *multicollinearity*. When different predictors correlate strongly, it raises the risk of missing a significant effect in the model because the model cannot differentiate between the predictors.[3] As a result, some usage variables were eliminated from consideration (see Appendix D for details). The final set of courseware usage and performance variables selected for the model appears in Table 6.

Table 6: *courseware usage and performance predictor variables entered into the final model*

ASU assignment types	Rio Salado assignment types

[3] The idea of multicollinearity is that some predictors may be so strongly related that it is hard to tell which of them have a significant predictive effect. Borrowing from medical research, height and weight are very strongly correlated. If you use predictive models with both height and weight in them, the models may not show any significant predictive effects for either height or weight because the model cannot separate the two. However, if you put only one of height or weight in the model, you might see a rather strong predictive effect. This generalizes to the idea that sometimes no individual predictor will highly correlate with another individual predictor, but three predictors together may make a fourth predictor mostly redundant. In this case, including that fourth predictor results in a poor model prediction, so removing it is advisable.

• Quiz attempts • Quiz score • QuizMe attempts • QuizMe score • Test attempts • Test score • Learning objectives mastered	• Homework hours • Homework attempts • Homework score • Learning objectives attempted • Learning objectives mastered

Standardization and variable centering were used to aid in the interpretation of model results. Pearson Education provided standardized average scores for student performance in all course activities in MyLab Math and MyLab Foundational Skills, and SRI analysts standardized prior achievement scores for ASU and Rio Salado College.[4] The SRI analysts also grand mean centered usage variables related to time and attempts in courseware activities and learning objectives attempted and mastered. This was to allow for more meaningful interpretation of model intercepts.[5] Descriptive statistics for all variables included in the regression models are in Appendix C.

Examining relations between Pearson courseware usage and performance, and course grades

For each institution, a numeric course grade outcome measure was created by converting the letter grades assigned by instructors to grade points.[6] SRI analysts explored the use of two different models to examine the relation between the Pearson usage / performance variables, and course grade, while controlling for student-level background characteristics. That is, a single-level model (SLM) of students only and a hierarchical linear model (HLM) that nested students (Level 1) by instructor (Level 2) (see Table 7 for ASU and Table 8 for Rio Salado). For both institutions, the HLM models indicated that instructors accounted for a significant amount of the variance in course grade, ranging from 10.9% of the variance at ASU, to 8% of the variance at Rio Salado. This suggests that the results from the HLM models are most appropriate for interpreting the relations of interest.[7, 8]

ASU

Both attempts at completing MyLab Math activities (specifically quizzes and tests activities) and the performance variables of learning objectives mastered, test scores, and quiz scores were associated with higher course grades, when controlling for student-level background characteristics (Table 7). These relations were statistically significant. Specifically, each additional Quiz attempt (a centered variable) was associated with a

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[4] Different institutions used different prior learning assessment instruments with different score scales. To permit comparison and more precise estimation, researchers transformed the score scales into comparable, standardized units. To standardize assessment scores, researchers transformed all prior achievement variables into a *z* score distribution (e.g., where mean = 0 and the standard deviation = 1). To transform into *z* scores, the sample mean was subtracted from each individual's score and then the difference was divided by the sample's standard deviation. Thus transformed, each student's score then represented how many standard deviation units the score differed from the sample mean (e.g., a one-unit increase in the standardized predictor variable equaled an increase of 1 standard deviation). This transformation also aided in the precise estimation and interpretation of regression intercepts by creating a meaningful zero value for the predictor (e.g., it is the mean of the distribution).

[5] Grand mean centering is a method of more precise estimation in multilevel modeling by transforming variables so that zero becomes the mean. For example, let us say that student age is being used as a predictor for a college curriculum study. There is nothing meaningful about students who are 0 years old. However, by centering, 0 now represents the mean age of the sample (20 years old) and an increase or decrease of 1 unit indicates the value for students who are 1 year older or younger than the sample mean.

[6] A+ = 4.3, A = 4.0, A-= 3.7, B+ = 3.3, B = 3.0, B-= 2.7, C+ = 2.3, C = 2.0, C- = 1.7; D+ = 1.3, D = 1.0, D- = 0.07; F = 0.

[7] The Level 1 intercept represents the average grade for the "reference student." For the ASU analysis, the reference student was a male from an overrepresented population (Asian or White), not a Pell recipient, with part-time enrollment, average pretest score; average hours on Quizzes, QuizMe, and Tests; average Quiz, QuizMe and Test scores; and an average number of objectives mastered. This reference student would be predicted to receive an end-of-course grade of 2.03, or approximately a C on the 4-point grade scale.

[8] For the Rio Salado analysis, the reference student was a male from an overrepresented ethnic population (Asian or White), not a Pell recipient, with part-time enrollment, average pretest score, average Test attempts, average Test hours, average Test scores, and average numbers of objectives attempted and mastered. This reference student would be predicted to receive an end-of-course grade of 2.69, or approximately a B- on the 4-point grade scale.

small increase of 0.013 grade point in students' end-of-course grades, or, approximately, a 0.13 grade point increase for students who made 9.89 attempts or more than the average student on quiz activities (1 standard deviation of quiz attempts = 9.89 attempts; see descriptive statistics in Table 4). Each additional test attempt (a centered variable) was associated with an increase of 0.26 grade point in students' end-of-course grades, or a 0.21 grade point increase for students who made 0.79 more attempts than the average student on test activities (1 standard deviation of test attempts = 0.79 attempts; see descriptive statistics in Table 4). However, attempts at completing QuizMe activities were associated with lower course grades. Each additional QuizMe attempt (a centered variable) was associated with a decrease of 0.004 grade point in students' end-of- course grades, or a 0.13 grade point decrease for students who made 32.13 more attempts than the average student on QuizMe activities (1 standard deviation of QuizMe attempts = 32.13 attempts; see descriptive statistics in Table 4).

In addition, we found that students' scores on quizzes, tests, and the number of learning objectives mastered were associated with statistically significant increases in course grade.

Table 7: *results of models examining the relation between MyLab Math usage and performance variables, and course grades at ASU*

Predictors	**Model 1 single-level model** β	**Model 2 hierarchical linear model** β
ALMAP predictors		
Gender (female = 1)	0.060	0.077**
Race/ethnicity (URP = 1)	-0.039	-0.031
Pell (yes = 1)	0.022	0.020
Full-time status (yes = 1)	0.012	-0.010
Pretest (ALEKS, standardized)	0.049**	0.026
Pearson courseware predictors[a]		
Quiz attempts (centered)	0.0129***	0.0129***
Average quiz score (standardized)	0.254***	0.262***
QuizMe attempts (centered)	-0.0047***	-0.0036**
Average QuizMe score (standardized)	-0.169***	-0.136***
Test attempts (centered)	0.324***	0.260***
Average test score (standardized)	0.908***	0.964***
Learning objectives mastered (centered)	0.0367***	0.0343***
Female	(0.0319***)	(0.0301***)
Male	(0.0419***)	(0.0390***)
Level 1 intercept	2.063***	2.027***
Level 2 intercept	—	0.040***
Student *n* (Level 1)	1,550	1,550
Instructor *n* (Level 2)	—	11
R^2	0.763	—

Note: URP = Underrepresented populations: non-White or non-Asian.
$*p < .05$, $**p < .01$, $***p < .001$.
[a] Gender interactions were tested with all Pearson use variables. Only gender interactions with significant

differences between female and male students are reported.

With respect to performance metrics, positive relations with course outcomes were found. Each standard deviation increase in a student's quiz score was associated with a 0.26 grade point increase in a student's course final grade, compared with a 0.96 increase for a 1 standard deviation increase in a student's average test score. Finally, each additional learning objective mastered (a centered variable) was associated with an increase of 0.034 grade point, or a 0.43 grade point increase for every 12.7 learning objectives mastered (which represents a 1 standard deviation increase in learning objectives mastered; see descriptive statistics in Table 4). However, each standard deviation increase in QuizMe scores was associated with a 0.14 grade point decrease in a student's course grades, or a 1.3 grade point decrease for every 9.54 points increase in a student's QuizMe score (which represents 1 standard deviation decrease in QuizMe score; see descriptive statistics in Table 4).

We did not find any statistically significant effects on course grades based on the interaction between gender and Pearson usage for ASU students (i.e., the relations were similar for male and female students).

Rio Salado

For Rio Salado and our examination of the relations between use of MyLab Foundational Skills and course grades, the model results show statistically significant and positive relations for both homework attempts and learning objectives mastered, and a small negative relation for learning objectives attempted (Table 8). Each additional Homework attempt was associated with an increase in a student's final course grade of 0.01 grade point, or an increase of 0.38 grade point for a 1 standard deviation increase in homework attempts (1 standard deviation in homework attempts is 38.31 attempts; see descriptive statistics in Table 5). We found contrasting relations for *attempting* a learning objective, compared with *mastering* a learning objective. Each additional learning objective *attempted* was associated with a *decrease* in final course grade of 0.01 point, or 0.85 grade point for a 1 standard deviation increase in learning objectives attempted (1 standard deviation was 85.13 objectives attempted; see descriptive statistics in Table 5). In contrast, each additional learning objective *mastered* corresponded to an *increase* of 0.013 grade point or 0.9 grade point for a 1 standard deviation in learning objectives mastered (1 standard deviation was 69.31 objectives mastered; see descriptive statistics in Table 5).

Table 8: *results of models examining the relation between MyLab Foundational Skills usage and performance variables, and course grades at Rio Salado*[b]

Predictors	**Model 1 single-level model *β***	**Model 2 hierarchical linear model *β***
ALMAP predictors		
Gender (female = 1)	-0.0164	-0.0342
Race/ethnicity (URP = 1)	-0.320*	-0.267*
Pell (yes = 1)	-0.273*	-0.230
Full-time status (yes = 1)	0.189	0.163
Pretest (Accuplacer Essay, standardized)	0.0379	0.000529
Pearson courseware predictors[a]		
Homework attempts (centered)	0.0109***	0.0105***
Homework hours (centered)	-0.000578	-0.00134

Average homework score (standardized)	-0.0245	0.0130
Learning objectives attempted (centered)	-0.0105***	-0.0102***
Learning objectives mastered (centered)	0.0122***	0.0134***
Level 1 intercept	2.742***	2.693***
Level 2 intercept	—	.0907*
Student *n* (Level 1)	296	296
Instructor *n* (Level 2)	—	8
R^2	0.63	—

Note: URP = underrepresented populations, referring to non-White or non-Asian populations.
* *p* <.05, ***p* <.01, ****p* <.001.
[a] Gender interactions were tested with all Pearson use variables. Only gender interactions with significant differences between female and male students are reported.
[b] Although the MyLab Foundational Skills product includes both mathematics and English skills, Rio Salado used it for the English skills only.

We did not find any statistically significant effects on grades of the interaction between gender and any of the Pearson use variables for Rio Salado students (i.e., the relations were similar for male and female students).

Examining relations between Pearson courseware usage and performance and course completion

To predict the likelihood of course completion (i.e., passing a course) based on courseware use and performance measures, SRI analysts, again, ran two different regression models: a single-level model (SLM) and a multilevel logistic model (MyLab Math) that had students at Level 1 and instructors at Level 2, paralleling the HLM models described in the previous section. However, because of issues with the MyLab Math models, we present results from the single-level model only.[9]

Course completion was coded as a dichotomous variable (i.e., completed vs. non-complete with completed defined as receiving a grade of C- or better). We report the relations associated with courseware usage variables in terms of odds ratios, which represent the odds that an outcome will occur given a particular condition, compared with the odds of the outcome occurring in the absence of that condition. In this case, an odds ratio greater than 1 indicates that the predictor variable was associated with an *increased* likelihood of course completion, and an odd ratio lower than 1 indicates that the predictor variable was associated with a *decreased* likelihood of course completion. For example, an odds ratio of 1.5 indicates that the odds of completing the course increase by a factor of 1.5, or 50%, for each one unit increase in the courseware use (hours), or performance in a courseware activity (standardized scores).

Tables 9 and 10 present the results for ASU and Rio Salado, respectively. (We report logistic regression model fit statistics in Appendix E.)

ASU

For the ASU sample using MyLab Math, the results indicate that increased quiz attempts and test attempts, increased average quiz and test scores, and increased learning objectives mastered were associated with increases in students' chances of completing a course (controlling for all other variables in the model, including student characteristics) — Table 9. Each additional quiz attempt was associated with an increase of

[9] The MyLab Math modeling issues were most likely related to multilevel sample size because logistic MLMs often require significantly larger sample sizes at both Levels 1 and 2 compared with HLMs.

3% in a student's odds of completing the course.[10] Each standard deviation (*SD*) increase in a student's average quiz score (*SD* = 16.27; see Table 4) was associated with an increase of 88% in that student's odds of completing the course. Each additional learning objective mastered was associated with a 19% increase in a student's odds of course completion. The strongest statistically significant positive relation found was the link between test scores and students' chances of completing a course. A 1 standard deviation increase in test scores (*SD* = 16.11) increased a student's odds of completing the course by a factor of 36 (odds ratio = 35.88).[11] We found one statistically significant negative association: increases in average QuizMe scores were negatively associated with completing the course. A 1 standard deviation increase in QuizMe scores (9.53) was associated with a decrease of 69% in students' odds of completing the course.

Finally, the interaction effect between gender and quiz attempts, test attempts, test scores, and learning objectives mastered was statistically significant. Female students' odds of passing a course increased relative to males with test attempts, test scores, and learning objectives mastered. Male students making more quiz attempts had a positive association with course completion.

Table 9*: results of models examining the relation between MyLab Math usage and performance variables, and course completion at ASU*

Predictors	Single-level model ***odds ratios***
ALMAP predictors	
Gender (female = 1)	1.044
Race/ethnicity (URP = 1)	0.933
Pell (yes = 1)	1.105
Fulltime status (yes = 1)	2.167
Pretest (ALEKS, standardized)	0.845
Pearson courseware predictors[a]	
Quiz attempts (centered)	1.034*
(Female)	(0.991)
(Male)	(1.063**)
Average quiz score (standardized)	1.875**
QuizMe attempts (centered)	0.987
Average QuizMe score (standardized)	0.315***
Test attempts (centered) (Female) (Male)	3.313*** (5.864***) (2.159**)
Average test score (standardized)	35.88***
(Female)	(95.568***)
(Male)	(18.593**)
Learning objectives mastered (centered)	1.187***
(Female)	(1.250***)

[10] The percentage odds figures were drawn from the table by rounding to the nearest hundredth of a decimal unit. For example, the centered Quiz attempts odds ratio of 1.034, was rounded to 3%.

[11] We did not have sufficiently detailed information about the implementation of the courseware at ASU to explain this effect. We speculate that one possible explanation for this relatively strong relation between Test scores and the odds of completing the course may be that instructors weighted students' courseware Test scores in the computation of the final course grade, but we cannot confirm that notion for certain.

(Male)	(1.150***)
Constant	2.169*
Students	1,550
Pseudo R^2	0.661

Note: URP = Underrepresented populations: non-White or non-Asian.
*p < .05, ** p< .01, ***p < .001
[a]Gender interactions were tested with all Pearson use variables. Only gender interactions with significant differences between female and male students are reported.

Rio Salado

For Rio Salado students using MyLab Foundational Skills, the results indicated that increased homework attempts and learning objectives mastered were associated with greater odds of course completion (Table 10). Each additional homework attempt was associated with a 6% increase in the odds of course completion. Each additional learning objective mastered was associated with a 3% increase in the odds of successfully completing the course.[12] However, we also found that each additional learning objective attempted was associated with a 3% reduction in a student's odds of completing a course.

We did not find any statistically significant predictive interaction effects on the likelihood of course completion between gender and any of the Pearson use variables for Rio Salado students (i.e., the relations were similar for male and female students).

Table 10: *results of models examining the relation between MyLab Foundational Skills usage and performance variables, and course completion at Rio Salado*

Predictors	single-level model ***odds ratios***
ALMAP predictors	
Gender (female = 1)	1.122
Race/ethnicity (URP = 1)	0.469
Pell (yes = 1)	0.474
Fulltime status (yes = 1)	1.371
Pretest (Accuplacer essay, standardized)	1.243
Pearson courseware predictors[a]	
Homework attempts (centered)	1.059***
Homework hours (centered)	1.006
Average homework score (standardized)	1.653
Learning objectives attempted (centered)	0.971***
Learning objectives mastered (centered)	1.30***
Constant	3.574*

[12] The percentage odds figures were drawn from the table by rounding to the nearest hundredth of a decimal unit. For example, the centered odds ratio for learning objectives mastered of 1.03 was rounded to 3%.

Students	296
Pseudo R^2	0.647

Note: URP = Underrepresented populations: non-White or non-Asian.
$*p < .05$, $**p < .01$, $***p < .001$.
[a] Gender interactions were tested with all Pearson use variables. Only gender interactions with significant differences between female and male students are reported.

Conclusion

This study aimed to deepen understanding of the relation between courseware activity usage and course outcomes. SRI used the ALMAP course outcome data collected over two to three academic terms from Arizona State University and Rio Salado College from 2014 through 2015, focusing on a subset of the original participants for whom matching Pearson usage data could be obtained. That is, 1,570 ASU students who attended traditional face-to-face classes, and 327 Rio Salado students who studied online. The hierarchical models in this study controlled for student background characteristics common to educational research, including gender, Pell grant status and incoming skill level.

Courseware usage and performance trends by institution

- During each of each of two 17-week academic periods at Arizona State University (ASU), each student spent an average total of 32 hours in the MyLab Math courseware. Most time was spent in QuizMe, the automated quiz activity in the MyLab Math Study Plan. QuizMe checks knowledge either (1) after students engage in practice activities, or (2) before students engage in practice, to document competency and permit skipping redundant practice activities. SRI did not have any usage data from Study Plan practice activities, which are distinct from homework activities. Nearly two-thirds of ASU students did not do homework activities in MyLab Math. On average, ASU students made about 80 attempts over the full course in QuizMe. Across the ASU's students' three primary activity types for which SRI had usage and performance data — quizzes, QuizMe quizzes and tests — the average performance score was 69%. On average, students attempted 52 learning objectives and mastered 51 of them, based on data from the Study Plan's QuizMe quizzes.
- Over each of Rio Salado's three 13-week academic periods, each student spent an average total of 18.8 hours in MyLab Foundational Skills courseware. On average, Rio Salado students made about 103.6 attempts at homework assignments over the full course. On average, Rio Salado students made about 32.89 test attempts per academic term. The average Rio Salado student's score across the three primary activity types — homework, quizzes, and tests — was 91%. On average, they attempted 229 learning objectives, but mastered only about 124 of them, based on data aggregated across homework, quizzes, and tests.

Predicting course outcomes from usage data

Controlling for student background characteristics common to educational research, several courseware usage and performance variables significantly predicted the two course outcomes at each institution: course grades and completion. In exploring the usage data, however, SRI discovered many high correlations and multicollinearity issues that prevented full use of all activity types and usage metrics (e.g., hours, attempts) in our predictive models (for more details, see Appendix D). For ASU, we were unable to include both hours and attempts because of multicollinearity issues, so in consultation with Pearson, we chose to use attempts as our preferred usage variable. For Rio Salado, the activity types were so highly correlated that we were able to include only one activity type. In consultation with Pearson, we chose to use homework as our preferred activity variable. In the case of ASU, we included all activity types except homework because too few students used those activities in the courseware.

MyLab Math at ASU:

- **Course grades:** the model showed that three usage and performance trends — increased attempts on quizzes and tests, increased average scores on quizzes and tests, and increased learning objectives mastered — were associated with significantly higher course grades, when controlling for the selected student-level background characteristics. However, having a greater number of MyLab Math QuizMe attempts and achieving better scores in QuizMe activities in the Study Plan were associated with statistically significant lower course grades, when controlling for student-level background characteristics.
- **Course completion:** the model showed that three usage and performance trends — increased attempts in quizzes and tests, increased average scores on quizzes and tests, and increased learning objectives mastered — were associated with an increased likelihood of students completing a course, controlling for the selected student-level background characteristics. In addition, female students who made more test attempts, scored higher on the tests, or mastered more objectives were more likely to pass their courses than males. Male students who made more quiz attempts were more likely to pass their courses than females. Finally, one negative association was found between performance in the courseware and course completion: increases in the average QuizMe scores were negatively associated with completing the course.

MyLabFoundational Skills at Rio Salado:

- **Course grades:** both a higher number of homework attempts and a higher number of learning objectives mastered, based on aggregate data from homework, quizzes, and tests, were associated with statistically significant higher course grades, when controlling for the selected student-level background characteristics. There was a negative association between attempting learning objectives and course grades.
- **Course completion:** the model results with course completion as the outcome variable mirror those for course grades. Making more homework attempts and mastering more learning objectives within the courseware is associated with an increased likelihood of completing courses, after controlling for the selected student-level background characteristics. However, we also found that the more learning objectives attempted was associated with a lower likelihood of completing the course.

In summary, after controlling for the selected student demographics and prior knowledge, both *practice* with some MyLab features — homework, quizzes, tests, and *mastering* learning objectives — were predictive of improved course grades and passing courses.

Discussion

Against the backdrop of the college completion agenda that seeks to increase the number of students who obtain a work-relevant credential or degree though postsecondary education (Bailey, 2009), U.S. institutions of higher education are increasingly using courseware technologies to help students study. Such technologies include electronic textbooks that feature automatically graded homework assignments, quizzes, and practice tests. Designers of interactive electronic textbooks intend to engage students in these activities to help them achieve content mastery. However, initial research indicates that both students and faculty members engage in different degrees of courseware usage, which leads to different impacts on student course outcomes. Understanding the relationship between courseware activity usage and course outcomes has the potential to provide educators and courseware developers with better evidence on how to optimize implementation of courseware technologies.

The analyses conducted in this study assess the courseware usage trends that are predictive of students attaining higher course grades and passing courses. This study is based on data gathered from 19 English courses at Rio Salado from three terms between 2014 and 2015, and 72 mathematics courses at ASU from two terms in 2014. The study presents descriptive statistics and inferential statistical models that use the courseware usage and performance data to predict course grades and course completion (i.e., passing a course). The models controlled for student background characteristics, including student gender, ethnicity, Pell status, enrollment status (full time or part time) and measures of student prior achievement or a proxy, when available. Since analyses revealed a high degree of correlation among the courseware activity variables, analysts consulted with Pearson to select the variables of interest to include in the models reported here.

One high-level take-away from this study is that practicing with content until one gets individual homework problems, quiz items, and test items correct appears to lead to positive course outcomes. The study also raises questions about the value of alternative uses of the courseware, such as attempting a larger number of learning objectives than one intends to master (in the case of Rio Salado) or relying on the Study Plan's QuizMe quizzes without engaging in practice activities (in the case of ASU). These alternative practices did not appear to yield positive impacts on course performance. However, we cannot say for certain whether either of these conclusions are accurate without usage data from the Study Plan's practice activities and more information about how, and whether, faculty members integrated the courseware scores for learning objectives mastered into their course grades. Also, the study could not determine to what extent these alternative practices occurred as students responded to recommendations from an outside vendor's adaptive algorithms, as the vendor's usage data was insufficient for interpretation.

Overall, the findings indicate that future studies exploring MyLab courseware usage data would be enhanced by collection of class implementation details about (1) the specific MyLab courseware activities that instructors assign, (2) their methods of integrating the courseware scores into class grading systems, and (3) the assumptions that both students and instructors make about how to use the MyLab courseware to support learning. Of particular interest is building an understanding of how instructors guide students to engage in the courseware activities, specifically homework, quizzes, and tests, and, in the case of MyLab Math, understanding the trade-offs of replacing engagement in these three activities with a Study Plan that emphasizes practice activities and QuizMe quizzes. Future studies also should include usage data from all features of the system, including practice activities in the Study Plan.

However, the results show negative relations for both QuizMe attempts and QuizMe scores with course grades. Without more detailed usage data focused on behaviors associated with productive persistence, this outcome cannot be interpreted definitively. However, we speculate that this outcome likely stems from student efforts to "game" the Pearson courseware and not engage in productively persistent learning activity. For example, a high average number of QuizMe attempts and low course outcomes is consistent with students who skip practice activities, and instead, repeatedly take guesses at QuizMe quizzes until they achieve a passing score. This behavior drives up the number of QuizMe attempts. However, students have not necessarily learned the material, which shows in lower course grades. On the other hand, obtaining higher QuizMe scores and low course outcomes may stem from two types of behavior: one consistent with gaming the system and one consistent with productive persistence. Students attempting to game the system may pursue a limited number of learning objectives and achieve high average scores on those few QuizMe quizzes, but have not covered enough material to do well in the course. However, more persistent students may attempt a higher number of learning objectives and achieve a lower average QuizMe score, but have covered sufficient material to do well in the course.

This study provides some further information on how to control for variations in students' baseline knowledge. In a past internal MyLab Math study (Pearson Education, 2016), analysts used prior term grades as a baseline knowledge measure with a subset of students. Using this as the prior achievement variable, Pearson analysts found that the number of courseware learning objectives mastered failed to predict passing a course. However, when the current study used college entrance examination scores as a baseline knowledge measure (e.g., as part of the ALMAP study), it found that the number of learning objectives mastered in MyLab Math courseware not only predicted passing the course, but also predicted higher course grades. These contrasting results raise questions about the analyses that use prior GPA as opposed to standardized test scores as proxies for prior achievement. A third option for establishing prior knowledge used in the ALMAP study was found to be most precise: using an assessment of prior knowledge on the academic content relevant to a particular course. The study also provides some support for the theory advanced in the prior internal MyLab Math report that homework and quizzes can help students master the course material. In the current study of MyLab Math, higher attempts (e.g., more practice) with quiz items (and test items) significantly predicted higher course grades and passing the course.

For MyLab Foundational Skills, this study indicated a negative relation between learning objectives attempted and both course completion and grades. Further, there was the wide gap between the number of learning objectives *attempted* by the Rio Salado students and those they *mastered* within the courseware. We should note that Rio Salado students were receiving Study Plan guidance from the outside vendor's adaptive algorithm, but how and when they were using those recommendations was not interpretable from the algorithm data available for this analysis. Without more algorithm usage data and classroom implementation data — such as how instructors incorporated courseware scores toward course grades, or how students were responding to recommendations to pursue specific learning objectives — it is difficult to interpret these findings. It is unclear in the case of MyLab Foundational Skills whether students were exploring extra learning objectives out of curiosity, or because they failed to understand how to navigate through the courseware and how to respond to the outside vendor's adaptive algorithm recommendations.

There are several limitations to this study. In the models, we attempted to control for any bias that could be introduced by students' background characteristics and prior skill level by including measures of background characteristics (e.g., gender, Pell grant status) and incoming skill level. Despite these controls, these measures most likely did not capture all the possible confounding factors that might influence use and course outcomes, such as student motivation, family support, and prior learning experiences with technology. As a result, while results of these analyses can help indicate whether a relationship between use and learning outcomes exists, they cannot be used to establish with certainty whether product use caused better student leaning outcomes. There are multiple plausible explanations for any of the reported associations. Thus, the findings associated with these analyses should be treated as exploratory and positive associations as promising but not definitive evidence of a causal connection between product use and improved learning and skill development.

In addition, the samples at each campus in this study were smaller than those in the original ALMAP study because for these analyses, researchers needed to match students in the ALMAP sample with their Pearson courseware usage data. For a variety of reasons, it was not possible to match data in many cases in the two data sets. Thus, the original ASU sample of 2,475 was reduced to an analytical sample of 1,570, and the original Rio Salado sample of 964 was reduced to 327. The resulting student samples varied demographically across the two institutions. ASU students were evenly split between men (46%) and women (54%), were mostly White and Asian (61%), were full-time students (95%), and less than a third relied on Pell grant financial aid. In contrast, Rio Salado students were mostly women (63%), were more representative of diverse races/ethnicities (48% White or Asian; 43% other populations), were enrolled mostly part time (73%), and more than half relied on federal Pell grant assistance.

Another limitation is that not all instructors participated in the ALMAP surveys, and those surveys did not focus specifically on elements of the MyLab Pearson products. However, some of the items did shed light on specific implementation challenges. For example, ASU instructors noted that students “rushed through” the courseware content and focused on “getting the points”, rather than deeply learning. The Rio Salado instructors said they had difficulty importing grades from MyLab Foundational Skills into their online grading system, inserting customized writing assignments into the courseware, and providing feedback to students. They also described their students as not being “savvy” to the system and failing to find required writing assignments in the system. Faculty respondents did all note that they could track individual and class progress using the courseware.

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Appendix A: Data Audit Findings

These findings, which were reported in the Interim Report submitted to Pearson in February 2017 and March 2017 are included here for completeness.

Table A1: *ASU data audit report*

Pearson courseware variable	***N* of student data available**
Student total time spent (hrs) on MyLab Math / MyLab Foundational Skills homework	1570 (Non-missing values for 582 records only; all other records set to 0)
Student total number of homework attempts	1570 (Non-missing values for 582 records only; all other records set to 0)
Student standardized MyLab Math / MyLab Foundational Skills homework grade	582
Student total time spent (hrs) in MyLab Math / MyLab Foundational Skills test	1570
Student total number of test attempts in MyLab Math / MyLab Foundational Skills	1570
Student standardized MyLab Math / MyLab Foundational Skills test grade	1547
Student total time spent (hrs) in MyLab Math / MyLab Foundational Skills quiz	1570
Student total number of quiz attempts in MyLab Math / MyLab Foundational Skills	1570
Student standardized MyLab Math / MyLab Foundational Skills quiz grade	1550
Student QuizMe hours spent	1570
Student QuizMe attempts	1570
Student QuizMe standardized grade	1517
Number of unique MyLab Math / MyLab Foundational Skills objectives attempted	1570
Number of MyLab Math / MyLab Foundational Skills objectives mastered	1570
Evidence of outside vendor's product being turned on in course (plus timestamp)	No timestamps in the aggregated file
Evidence of outside vendor's product recommendations followed (note: really received)	1570

ALMAP variables	***N* of student data available**
Gender	1570
Race / ethnicity	1550

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Pell eligible	1570
Full time / part time status	1570
Prior knowledge	1518
Completion	1570
Grade value	1570

Table A2: *Rio Salado data audit report*

Pearson courseware variable	***N* of student data available**
Student total time spent (hrs) on MyLab Math / MyLab Foundational Skills homework	326
Student total number of homework attempts	327
Student standardized MyLab Math / MyLab Foundational Skills homework grade	327
Student total time spent (hrs) in MyLab Math / MyLab Foundational Skills test	327
Student total number of test attempts in MyLab Math / MyLab Foundational Skills	327
Student standardized MyLab Math / MyLab Foundational Skills test grade	327
Student total time spent (hrs) in MyLab Math / MyLab Foundational Skills quiz	327
Student total number of quiz attempts in MyLab Math / MyLab Foundational Skills	327
Student standardized MyLab Math / MyLab Foundational Skills quiz grade	321
Number of unique MyLab Math / MyLab Foundational Skills objectives attempted	327
Number of MyLab Math / MyLab Foundational Skills objectives mastered	327
Evidence of outside vendor's product being turned on in course (plus timestamp)	No timestamps
Evidence of outside vendor's product recommendations followed (note: really received)	327
Study objectives achieved	No data
Courseware outcomes	No data

ALMAP Demographic and Outcome Variables	***N* of student data available**
Gender	326
Race / ethnicity	297
Pell eligible	327
Full time / part time status	327
Prior knowledge	318
Completion	327
Grade value	319 with 8 W's (which were counted as 0s)

Appendix B: data processing details

Data files

SRI Analysts received a total of twelve different data files that correspond to six different data sources, organized by the following data types:

1. Pearson usage data (source: Pearson)
   a. Assignment data (one for ASU; one for Rio Salado)
   b. Learning objective data (one for ASU; one for Rio Salado)
   c. Outside vendor's product data (ultimately not used) (one for ASU; one for Rio Salado)
2. ALMAP data (source: SRI)
   a. Course outcomes + additional student background characteristics (e.g., ethnicity, Pell status, enrollment status, prior achievement
3. Additional data files (source: institutions of higher education)
   a. Linking files (e.g., that matched ALMAP student IDs to Pearson usage file student IDs) (ASU provided gender data inside its linking file)
   b. Separate gender data file (Rio Salado only)

Data cleaning

Pearson usage data cleaning:

ASU: no major cleaning actions were required.

Rio Salado: one major cleaning action was to deal with students enrolled in more than one course (See Table B1 below). In addition, problems with matching students to the Pearson usage data required dropping some students (See Table C1 in Appendix C). This was due to a lack of course IDs and / or inconsistent course IDs across the different Rio Salado, ALMAP, and Pearson data files. It was not possible to reliably discern which Pearson usage data corresponded to which ALMAP outcome data for many Rio Salado students. Therefore, these cases had to be dropped from the analysis.

Table B1: *the resulting number of "duplicate" students removed from each Pearson usage data file for Rio Salado*

Data File	**Initial *N***	***N* removed**	**Cleaned *N***
Assignment data	402	38	364
Learning objective data	409	52	357
Outside vendor's product data	415	54	361

ALMAP data cleaning:

SRI Analysts removed repeating students in the ALMAP data, which covered three school academic terms. To avoid misinterpretation based on practice effects, SRI analysts removed students who used the product in more than one term, keeping only those in their first term. Repeater students were identified in two ways:

1. If they were listed as a repeater by the indicator variable "repeater" in the ALMAP data file.
2. If the same student ID appeared in more than one term.

It is important to note that there were four terms of treatment students at ASU. However, ASU could only provide linking data for three of those terms. The three terms are dubbed "participating terms."

Table B2: *the cleaning activities and corresponding number of students removed for respective data files*

Data file	**Initial *N***	**Reason for removal**	**Lost *N***	**Cleaned *N***
ASU				
ALMAP data file	2,475	Non-participating term	121	2,354
		Repeaters	235	2,119
Linking file	2,354	Missing student ID	1	2,353
Rio				
ALMAP data file	1,027	Repeaters	64	963
Linking file	429	Duplicates	28	401
		Missing student ID	11	390
		Students had multiple different IDs	18	372
Merged Pearson usage files and ALMAP data file	342	ALMAP Control students (analysis focused on Treatment)	15	327

Data merging

Files from all five data sources had to be merged for the analysis. The order of merging operations was as follows:

1. Merge the ALMAP with linking files and gender files
2. Merge the Pearson assignment, learning objectives, and outside vendor's product data
3. Merge (1) and (2)

ASU: to merge, SRI analysts needed each student to have data from all three Pearson usage data file sources: assignment, learning objectives and outside vendor's product. In merging these files with the ALMAP data, it was discovered that, for an unknown reason, there were no data reflecting usage of either outside vendor's product or the Pearson MyLab Math QuizMe activity in the first ASU term. Therefore, the first term of ALMAP students was excluded.

Table B3: *number of students in each file type and number of students merged for ASU*

ASU Students	***N***
Per file type	
Assignment data	4,546
Learning objective data	4,467
Outside vendor's product data	3,376
ALMAP data	2,475
Linking data	2,353
Per data file merging step	
Students merged between ALMAP and linking data files	2,118
Students merged among Pearson assignment, learning objective, and outside vendor's product data files	3,346
Students merged among ALMAP, linking data, and Pearson data files	**1,570**

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Table B4: *number of students in each file type and number of students merged for Rio Salado*

Rio Salado Students	***N***
Per file type	
Assignment data	364
Learning objective data	357
Outside vendor's product data	361
ALMAP data	964
Gender data	899
Linking data	372
Per data file merging step	
Students merged between ALMAP and linking data files	372
Students merged among Pearson assignment, learning objective, and outside vendor's product data files	357
Students merged among ALMAP, linking data, and Pearson data files	**327**

While the outside vendor's product data was ultimately not included in the present study because of quality concerns, SRI analysts decided to include outside vendor's data as a required element of the data merging process. The reason for this decision is as follows. First, SRI analysts determined that all Rio Salado students used courseware with the outside vendor's adaptive learning features, while only some ASU students used courseware with outside vendor's adaptive learning features. Based on this finding, SRI analysts decided that, in order to support clearer cross-institution and cross-product comparisons, all students included in any analysis for this study would have had access to the outside vendor's product (i.e., they were listed in the vendor's data file). This decision had a significant effect on the ASU analytic sample, removing approximately 400 students from consideration (all from one of two ALMAP Term 1 sub-samples). SRI analysts determined that the removal of 400 students would not have a significant effect on the statistical power at either Level 1 or Level 2 ASU regression analysis, given the current sample size (e.g., 1,570). The decision to require the outside vendor's data alignment had no effect on the ultimate Rio Salado analytic sample.

Appendix C: model descriptives of courseware usage and performance

Table C1: *model descriptive statistics for ASU Students*

Variable	***n***	**Mean**	***SD***	**Min**	**Median**	**Max**
ALMAP Predictors						
Gender (female = 1)	1570	0.54				
Ethnicity (URP = 1)	1550	0.38				
Pell (yes = 1)	1570	0.32				
Full-time status (yes = 1)	1570	0.95				
Pretest proxy (standardized)[a]	1570	0.00	1.00	-3.14	-.0.09	3.31
Pearson Use Data						
Homework						
Attempts	1570	0.49	0.71	0	0	2
Hours	1570	0.21	0.65	0	0	4.63
Average standardized score[b]	582	0.01	1.04	-0.66	-0.66	2.17
Quiz						
Attempts	1570	13.25	9.89	0	11	140
Hours	1570	10.89	7.37	0	9.615	57.69
Average standardized score[c]	1570	0.16	0.73	-2.85	0.28	1.70
QuizMe						
Attempts	1570	80.22	32.13	0	81	206
Hours	1570	17.86	9.68	0	17.025	76.29
Average standardized score[c]	1570	0.12	0.87	-3.01	0.09	3.68
Test						
Attempts	1570	4.46	0.79	0	5	7
Hours	1570	3.09	1.04	0	3	6.59
Average standardized score[c]	1570	0.31	0.75	-2.79	0.4	1.87
Learning Objectives						
Attempted	1570	51.84	12.04	1	58	87
Mastered	1570	50.50	12.70	1	57	61
ALMAP outcomes						
Course grade value	1570	2.40	1.26	0	2.23	4.33
Course complete (> C- = 1)	1570	0.78				

[a] This is the standardized version of the imputed pretest proxy variable (ALEKS)
[b]Too few observations to meaningfully impute; excluded from subsequent analyses.
[c] This variable includes imputed data for student records where it was missing.

Table C2: *model descriptive statistics for Rio Salado students*

Variable	***n***	**Mean**	***SD***	**Min**	**Median**	**Max**
ALMAP Predictors						
Gender (female = 1)	326	0.63				
Ethnicity (URP = 1)	297	0.48				
Pell (yes = 1)	327	0.58				
Full-time status (yes = 1)	327	0.27				
Pretest proxy (standardized)[a]	327	0.00	1.00	-4.60	0.40	5.40
Pearson use data						
Homework						
Attempts	327	103.64	38.31	0	111	230
Hours	327	11.03	11.82	0	8.51	120.08
Average standardized score[b]	327	0.12	0.47	-2.44	0.24	0.68
Quiz						
Attempts	327	19.69	7.32	0	22	32
Hours	327	3.82	4.79	0	2.33	35.54
Average standardized score[b]	327	-0.04	1.07	-4.93	0.41	0.41
Test						
Attempts	327	32.89	12.97	1	35	67
Hours	327	3.95	3.34	0.09	3.25	25.93
Average standardized score[b]	327	-0.01	1.03	-4.94	0.02	1.82
Learning objectives						
Attempted	327	228.58	85.13	144	209	518
Mastered	327	123.81	69.31	0	125	494
ALMAP outcomes						
Course grade value	327	2.48	1.66	0	3	4
Course complete (> C- = 1)	327	.70				

[a] This is the standardized version of the imputed Pretest variable. (Accuplacer Essay)
[b] This variable includes imputed data for student records where it was missing.

Appendix D: Correlation and Variance Inflation Factors

For both institutions, SRI analysts explored the correlations between students' Pearson usage variables (Tables D1, D3) and their variance inflation factors (VIF) (Tables D2, D4). To maximize the predictive value of the statistical models, analysts included only variables with (1) no correlations greater than |0.60| with other usage variables and (2) a VIF of under 5.00. The variance inflation factor of a predictor represents the degree to which a predictor coefficient's standard error is increased due to multicollinearity with other predictors in a standard ordinary least squares regression. In an ideal model, all predictors would have VIFs of 1.00, representing no increase in standard errors. VIFs above 5.00 suggest significantly inflated regression coefficient standard errors, which may lead to (1) false predictive negatives, meaning predictors may appear to have nonsignificant predictive effects when they actually have predictive effects, and (2) imprecise estimates of significant predictive effects.

For ASU:

After review, analysts removed the following variables from the ASU model:

- homework average Score from analysis because of missing data (see Tables C1, C2), so it does not appear in either table
- all homework variables because of correlation of 0.60 and absence of Homework Average Score
- all hours variables after consultation with Pearson and focus on attempts because it had greater interpretability
- learning objectives attempted because of a correlation greater than |0.60| with objectives mastered, exceeding the VIF threshold of 5.00, and a determination that objectives mastered was more important than objectives attempted.

For Rio Salado:

Analysts found that each of the three activity types (homework, quizzes and, tests) had at least one correlation with another activity type in excess of the |0.60| threshold, and had at least one usage variable in excess of the 5.00 threshold.

After review and consultation with Pearson analysts, researchers decided to remove the test and quiz usage variables from the model and to keep only the homework attempt usage variables. Homework was chosen because it had the greatest number of attempts and therefore seemed to represent student engagement better.

Table D1: *correlation matrix of Pearson use variables for ASU students*

	HW, attempts	HW, hours	Quiz, attempts	Quiz, hours	Quiz, ave score	QuizMe, attempts	QuizMe, hours	QuizMe, ave score	Test, attempts	Test, hours	Test, ave score	Obj. attempted	Obj. mastered
HW, attempts	1												
HW, hours	0.5760	1											
Quiz, attempts	0.0752	0.0266	1										
Quiz, hours	0.1153	0.0741	0.7539	1									
Quiz, ave score	0.0852	0.0861	-0.1241	0.109	1								
QuizMe, attempts	0.0624	0.0278	0.3391	0.373	-0.0017	1							
QuizMe, hours	0.0471	0.0437	0.1357	0.301	0.0080	0.6615	1						
QuizMe, ave score	0.0730	0.0851	-0.1535	-0.100	0.2383	-0.6377	-0.3639	1					
Test, attempts	0.1703	0.1201	0.1788	0.202	-0.0816	0.2899	0.1935	-0.0166	1				
Test, hours	0.0786	0.0219	-0.0600	0.074	-0.0446	0.1273	0.3852	0.0476	0.3696	1			
Test, Ave Score	0.0447	0.0539	0.2533	0.356	0.4807	0.2138	0.1152	0.1451	-0.0263	0.0495	1		
Obj. attempted	0.1219	0.0977	0.2735	0.367	0.2734	0.5843	0.4620	0.0529	0.1659	0.1262	0.4696	1	
Obj. mastered	0.1293	0.1062	0.2799	0.379	0.2912	0.5647	0.4540	0.0985	0.1709	0.1196	0.4779	0.9822	1

Table D: *variance inflation factors (VIF) for ASU students*

Variable	**VIF**
ALMAP predictors	
Gender (Female = 1)	1.06
Ethnicity (URP = 1)	1.15
Pell (Yes = 1)	1.12
Full-time status (Yes = 1)	1.02
Pretest proxy (standardized)	1.08
Pearson use data	
Homework	
Attempts	1.54
Hours	1.53
Quiz	
Attempts	2.94
Hours	2.96
Average standardized score	1.64
QuizMe	
Attempts	7.37
Hours	2.43
Average standardized score	4.45
Test	
Attempts	1.50
Hours	1.51
Average standardized score	1.84
Learning objectives	
Attempted	30.35
Mastered	33.65
Mean VIF	**5.51**

Table D3: *correlation matrix of Pearson use variables for Rio Salado students*

	HW, attempts	HW, hours	HW, ave. score	Quiz, attempts	Quiz, hours	Quiz, ave. score	Test, attempts	Test, hours	Test, ave. score	Obj. attempted	Obj. mastered
HW, attempts	1										
HW, hours	0.4013	1									
HW, ave. score	0.4033	0.0948	1								
Quiz, attempts	0.9554	0.3933	0.4510	1							
Quiz, hours	0.3431	0.7253	0.0375	0.3646	1						
Quiz, ave. score	0.1984	0.1615	0.5683	0.1935	0.1388	1					
Test, attempts	0.9159	0.3834	0.3758	0.9144	0.3292	0.1734	1				
Test, hours	0.4446	0.7119	0.0924	0.4459	0.6389	0.1314	0.5334	1			
Test, ave. score	0.1612	-0.0425	0.7563	0.2008	-0.1249	0.2646	0.0330	-0.1523	1		
Obj. attempted	0.0195	-0.0597	-0.1522	-0.1387	-0.023	-0.0441	-0.1349	-0.0762	-0.1065	1	
Obj. mastered	0.7542	0.1882	0.4194	0.6680	0.1111	0.1613	0.6237	0.2297	0.3284	0.4087	1

Table D4: *variance inflation factors (VIF) for Rio Salado students*

Variable	**VIF**
ALMAP predictors	
Gender (Female = 1)	1.09
Ethnicity (URP = 1)	1.15
Pell (Yes = 1)	1.25
Full-time status (Yes = 1)	1.22
Pretest (standardized)	1.15
Pearson use data	
Homework	
Attempts	21.67
Hours	3.37
Average standardized score	5.91
Quiz	
Attempts	17.45
Hours	2.52
Average standardized score	1.93
Test	
Attempts	12.36
Hours	3.02
Average standardized score	4.74
Objectives	
Attempted	2.76
Mastered	5.51
Mean VIF	**5.44**

Appendix E: logistic regression accuracy tables

In addition to using pseudo R^2 to assess model fit for logistic regressions, SRI analysts reviewed predictive accuracy tables for each logistic regression. Tables E1 and E2 provide classification accuracy information organized by (1) students' actual course completion results based on the data and (2) students' predicted course completion results based on the predictive models. In general, logistic regression models will have three different accuracy rates, with 80+% accuracy indicating good model fit. SRI analysts reviewed three accuracy rates for each model as detailed below.

Correct classification rates can be calculated by the ratio of students correctly predicted in either condition (summed along the diagonal of the table) to the total number of students. The correct classification rate for ASU was 93% (1444/1550) (Table E1), and the correct classification rate for Rio Salado was 94% (278/296) (Table E2), indicating good model fit for both models.

Sensitivity, also known as the "true positive rate," can be calculated by the ratio of students correctly predicted to *complete*, to the total number of course *completers*. ASU (Table E1) has a sensitivity of 98% (1177/1206), and Rio Salado (Table E2) has a sensitivity of 99% (208/210), indicating good model fit for both models.

Specificity, also known as the "true negative rate," can be calculated by the ratio of students correctly predicted to *non-complete*, to the total number of course *non-completers*. ASU (Table E1) has a specificity of 78% (267/344), and Rio Salado (Table E2) has a specificity of 81% (70/86), indicating sufficient model fit for both models.

Table E1: *predictive accuracy for ASU*

	Actual course result		
Predicted course result	**Complete**	**Non-complete**	
Complete	1177	77	1254
Non-complete	29	267	296
	1206	344	1550

Table E2. *Predictive accuracy for Rio Salado*

	Actual course result		
Predicted course result	**Complete**	**Non-complete**	
Complete	208	16	224
Non-complete	2	70	72
	210	86	296

Appendix F: full model tables

Table F1: *results of models examining the relation between MyLab Math usage and performance variables and course grades at ASU*

Predictors	**Model 1 single-level model *B (SE)***	***p*-value**	**Model 2 hierarchical model *B (SE)***	***p*-value**
ALMAP predictors				
Gender (female = 1)	0.060 (0.032)	0.058	0.078 (0.030)	0.009
Race/ethnicity (URP = 1)	-0.040 (0.034)	0.244	-0.032 (0.032)	0.321
Pell (yes = 1)	0.022 (0.035)	0.539	0.021 (0.033)	0.536
Full-time status (yes = 1)	0.012 (0.070)	0.861	-0.010 (0.065)	0.876
Pretest (ALEKS, standardized)	0.049 (0.016)	0.002	0.026 (0.016)	0.094
Pearson courseware predictors				
Quiz attempts (centered)	0.013 (0.0018)	0.000	0.013 (0.0017)	0.000
Average quiz score (standardized)	0.25 (0.027)	0.000	0.262 (0.025)	0.000
QuizMe attempts (centered)	-0.005 (0.001)	0.000	-0.004 (0.0012)	0.002
Average QuizMe score (standardized)	-0.17 (0.038)	0.000	-0.136 (0.036)	0.000
Test attempts (centered)	0.32 (0.023)	0.000	0.260 (0.022)	0.000
Average test score (standardized)	0.91 (0.028)	0.000	0.964 (0.027)	0.000
Learning objectives mastered (centered)	0.037 (0.0024)	0.000	0.034 (0.0022)	0.000
Female	(0.032) (0.003)	0.000	(0.030) (0.003)	
Male	(0.042) (0.0035)	0.000	(0.039) (0.003)	
Level 1 intercept	2.06 (0.0701)	0.000	2.027 (0.090)	0.000
Level 2 intercept	—		.040 (0.018)	0.000
Student *n* (Level 1)	1,550		1,550	
Instructor *n* (Level 2)	—		11	
R^2	0.763		—	

Predictors	**Model 1 single-level model** ***B (SE)***	***p*-value**	**Model 2 hierarchical model** ***B (SE)***	***p*-value**
ALMAP predictors Gender (female = 1)	0.060 (0.032)	0.058	0.078 (0.030)	0.009
Race/ethnicity (URP = 1)	-0.040 (0.034)	0.244	-0.032 (0.032)	0.321
Pell (yes = 1)	0.022 (0.035)	0.539	0.021 (0.033)	0.536
Full-time status (yes = 1)	0.012 (0.070)	0.861	-0.010 (0.065)	0.876
Pretest (ALEKS, standardized)	0.049 (0.016)	0.002	0.026 (0.016)	0.094
Pearson courseware predictors Quiz attempts (centered)	0.013 (0.0018)	0.000	0.013 (0.0017)	0.000
Average quiz score (standardized)	0.25 (0.027)	0.000	0.262 (0.025)	0.000
QuizMe attempts (centered)	-0.005 (0.001)	0.000	-0.004 (0.0012)	0.002
Average QuizMe score (standardized)	-0.17 (0.038)	0.000	-0.136 (0.036)	0.000
Test attempts (centered)	0.32 (0.023)	0.000	0.260 (0.022)	0.000
Average test score (standardized)	0.91 (0.028)	0.000	0.964 (0.027)	0.000
Learning objectives mastered (centered)	0.037 (0.0024)	0.000	0.034 (0.0022)	0.000
Female	(0.032) (0.003)	0.000	(0.030) (0.003)	
Male	(0.042) (0.0035)	0.000	(0.039) (0.003)	
Level 1 intercept	2.06 (0.0701)	0.000	2.027 (0.090)	0.000
Level 2 intercept	—		.040 (0.018)	0.000
Student *n* (Level 1)	1,550		1,550	
Instructor *n* (Level 2)	—		11	
R^2	0.763		—	

Table F2: *results of models examining the relation between MyLab Foundational Skills usage and performance variables, and course grades at Rio Salado*

Predictors	**Model 1 single- level model *B (SE)***	***p*-value**	**Model 2 hierarchical level *B (SE)***	***p*-value**
ALMAP predictors				
Gender (female = 1)	-0.016 (0.126)	0.897	-0.034 (0.121)	0.778
Race/ethnicity (URP = 1)	-0.320* (0.124)	0.010	-0.267* (0.120)	0.027
Pell (yes = 1)	-0.273* (0.133)	0.040	-0.230 (0.128)	0.071
Full-time status (yes = 1)	0.189 (0.143)	0.187	0.163 (0.138)	0.240
Pretest (Accuplacer Essay, standardized)	0.038 (0.062)	0.538	0.0005 (0.061)	0.993
Pearson courseware predictors				
Homework attempts (centered)	0.011*** (0.003)	0.000	0.011*** (0.003)	0.000
Homework hours (centered)	-0.0006 (0.006)	0.922	-0.001 (0.006)	0.816
Average homework score (standardized)	-0.025 (0.153)	0.873	0.013 (0.156)	0.934
Learning objectives attempted (centered)	-0.011*** (0.001)	0.000	-0.010*** (0.001)	0.000
Learning objectives mastered (centered)	0.012*** (0.002)	0.000	0.013*** (0.002)	0.000
Level 1 intercept	2.742*** (0.132)	0.000	2.693*** (0.170)	0.000
Level 2 intercept	—		.0907*	0.022
Student *n* (Level 1)	296		296	
Instructor *n* (Level 2)	—		8	
R^2	0.63		—	

Table F3: *results of models examining the relation between MyLab Math usage and performance variables, and course completion at ASU*

Predictors	**SLM** ***odds ratios (SE)***	***p*-value**
ALMAP predictors		
Gender (female = 1)	1.044 (0.239)	0.850
Race/ethnicity (URP = 1)	0.933 (0.222)	0.771
Pell (yes = 1)	1.105 (0.272)	0.685
Fulltime status (yes = 1)	2.167 (0.970)	0.084
Pretest (ALEKS, standardized)	0.845 (0.103)	0.166
Pearson courseware predictors		
Quiz attempts (centered)	1.034* (0.0172)	0.046
(Female)	(0.991) (0.0264)	0.749
(Male)	(1.063**) (0.0243)	0.008
Average quiz score (standardized)	1.875** (0.354)	0.001
QuizMe attempts (centered)	0.987 (0.00745)	0.077
Average QuizMe score (standardized)	0.315*** (0.0845)	0.000
Test attempts (centered)	3.313*** (0.565)	0.000
(Female)	(5.864***) (1.635)	0.001
(Male)	(2.159***) (0.480)	0.000
Average test score (standardized)	35.88*** (10.29)	0.000
(Female)	(95.568***) (47.39)	0.000
(Male)	(18.593***) (6.671)	0.000
Learning objectives mastered (centered)	1.187*** (0.0210)	0.000
(Female)	(1.250***) (0.0392)	0.000
(Male)	(1.150***) (0.0260)	0.000
Constant	2.169* (0.969)	0.083
Students	1,550	
Pseudo R^2	0.661	

Table F4: *results of models examining the relation between MyLab Foundational Skills usage and performance variables, and course completion at Rio Salado*

Predictors	**SLM** *odds ratios (SE)*	***p*-value**
ALMAP predictors		
Gender (female = 1)	1.122 (0.594)	0.829
Race/ethnicity (URP = 1)	0.469 (0.232)	0.126
Pell (yes = 1)	0.474 (0.267)	0.185
Fulltime status (yes = 1)	1.371 (0.795)	0.587
Pretest (Accuplacer essay, standardized)	1.243 (0.306)	0.377
Pearson courseware predictors		
Homework attempts (centered)	1.059*** (0.015)	0.000
Homework hours (centered)	1.006 (0.025)	0.811
Average test score (standardized)	1.653 (1.173)	0.479
Learning objectives attempted (centered)	0.971*** (0.005)	0.000
Learning objectives mastered (centered)	1.030*** (0.008)	0.000
Constant	3.574* (2.301)	0.048
Students	296	
Pseudo R^2	0.647	