March 2017

MyLab Math

Efficacy Research Report

Open Ideas at Pearson
Sharing independent insights on the big, unanswered questions in education

Pearson

Contents

Product Summary

MyLab™ Math launched in July 2001 under the name MyMathLab. (The underlying product that enables the homework in MyLab Math, called MathXL, launched in the mid-1990s and continues to be an integral part in MyLab Math today). In Fall 2016 it was re-branded as MyLab Math. New iterations (feature enhancements added to MyLab Math) are released to the public for use twice annually (June and December), resulting in continual improvement of the system with new capabilities that support learning and teaching. MyLab Math is used primarily in the United States market, with around 3 million student registrations annually. This research report relates to the the most significant of the MyLab Math suite, MyLab Math, which has 1 million users per year.

MyLab Math is an online tutorial and assessment tool for teaching and learning mathematics. It is designed to provide engaging experiences and personalized learning so that each student can succeed and pass the course. It is predominantly used by first year students in Higher Education by learners who need remediation on foundational math skills before taking credit-level Math courses. This product is also used in K-12 (branded as MyLab Math for School) for Algebra 1, Algebra 2, Geometry, and dual-enrollment college-level courses.

MyLab Math's variety and large quantity of exercises — tied to the learner outcomes they support — regenerate algorithmically to give students multiple opportunities for practice on varying content. The exercises 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 also has adaptive resources such as a companion study plan and Skillbuilder exercises, to support personalized learning.

MyLab Math automatically tracks students' results, and includes item analysis to track classwide progress on specific learning objectives. MyLab Math is intended to enable a measureable impact on defined learner outcomes related to educational access, completion, competence, and progression. By providing every student a personalized remediation plan through the material and tracking progress at the objective level, MyLab Math aims to lower the student to instructor ratio: a feature that is especially important for the success of developmental mathematics students.

Intended Outcomes

One of the greatest challenges that US colleges 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 prealgebra, elementary algebra, and finally intermediate algebra, all of which must be passed before a student can enroll in a credit-bearing college mathematics course.

MyLab Math is designed to provide students with a positive learning experience and develop a positive mindset towards math so that they can achieve prerequisite math skills that will allow them to advance to, and successfully complete, credit-bearing mathematics courses.

The following are learner outcomes that have been agreed for the product based on internal research and validated with MyLab Math's customers. Our efficacy impact evaluation work (outlined in "Product Research" below) aims to provide evidence of MyLab Math's impact on these outcomes.

Intended Outcome 1: Learners have a positive learning experience
MyLab Math is designed to provide students with a positive learning experience. A variety of multimedia resources are available as assignment learning aids. Students can link to the ebook, video clips, and animations to improve their understanding of key concepts. All content in MyLab Math is derived from, or correlated to, an author's textbook, thereby building towards a seamless experience in class, in the book, and in MyLab Math.

Intended Outcome 2: Learners have a positive mindset to math
There are a variety of motivations, beliefs, and attitudes that may prevent students from achieving their potential. Specifically, three areas of importance are: dealing with anxiety, personal relevance, and mindset. These are areas where MyLab Math used in developmental math courses is aiming to help students, and mindset is a key outcome validated by instructors as being of importance to them and their students.

Intended Outcome 3: Learners complete tasks / activities / course on time
MyLab Math offers the opportunity to set prerequisites so that required parts of the course must be completed and passed before a student can go onto the next stage in his or her learning. MyLab Math exercises include learning aids, such as guided solutions, sample problems, and extra help at point-of-use, and also offer helpful feedback when students enter incorrect answers all designed to help students complete their assigned work. These learning aids can be activated or deactivated at the instructor's discretion.

Intended Outcome 4: Learners achieve a pass overall
The most obvious intended outcome for MyLab Math is to help learners improve in their math skills. MyLab Math has features such as Skillbuilder, which personalize learning based on student performance, providing recommendations on what skills students need to master to complete their assignments and improve skills specific to their needs and pass overall. The Companion Study Plan aims to support improved performance on tests by serving as a prerequisite check of all skills needed to do well on that test.

Intended Outcome 5: Learners complete the course and show success in subsequent courses
The majority of MyLab Math in developmental courses are offered at 2-year colleges in North America as a course or series of courses starting at basic arithmetic and then progressing through prealgebra, elementary algebra, and finally intermediate algebra. Students must demonstrate a readiness with these topics before enrolling in a credit-bearing college mathematics course. In addition to completing the developmental course, MyLab Math aims to help learners show success in subsequent courses.

Foundational Research

MyLab Math is aligned with the insights gained from over 30 years of research into intelligent tutoring systems (e.g. Ohlsson, 1986; Anderson, Corbett, Koedinger & Pelletier, 1995). In particular, it helps students to 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), by helping to focus students' attention on critical elements, and manage their load on working memory (Sweller & Cooper, 1985). All of these strategies and features are intended to enable students to succeed, often for the first time, in math, and so they begin to develop a positive mindset for mathematics. MyLab Math contextualizes all help functionality for developmental math students to help them succeed at solving the problem at hand. It is crucial for these students to establish a pattern of success in mathematics. The contextualized learning aids in MyLab Math help guide students to begin a positive journey through the material.

The design of MyLab Math is aligned with several areas of educational 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 Math demonstrates a number of these learning design principles:

Scaffolding with Worked Examples
There are a variety of learner support tools to help students struggling with assessment items (hints, videos, animations, etext), and students can "ask for help" and get step-by-step support in solving a math problem (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.

Supporting Student Success
Research has found a number of factors may be limiting students in achieving their potential. For example, some students lack foundational study skills or information about the kinds of behaviors that will help them to succeed in certain academic settings. MyLab Math includes "Student Success Resources" that provide additional support in these areas. By helping students manage anxiety (Maloney & Beilock, 2012), and providing training on study skills and test-taking strategies, among other topics, students are put on a path towards more self-regulated learning (e.g. Mega, Ronconi, & De Beni, 2014). In addition, students have access to materials that can help instill a "growth mindset," or belief that their abilities will improve with effort and practice (e.g., Yeager & Dweck, 2012; Dweck, 1996), which have been designed in consultation with leading researchers in the field.

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 if you can reduce extraneous cognitive load for students when they are reading or studying, you can improve the effectiveness of learning (Sweller, 1988). Put simply, if you remove distractions, 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 etext 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 above 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 mastery of skills and concepts based on student 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 suits their course structure and students' needs.

Intended Product Implementation

Over the past 10 years, educator studies completed by Pearson's customers have reported a variety of approaches to the implementation of MyLab Math. Within blended instruction models, students use MyLab Math to complete assigned reading and homework prior to class lectures and may then also complete chapter quizzes that account for 10% to 60% of their course grade.

In the emporium model, students use MyLab Math in computer labs or computer classrooms staffed by instructors, professional tutors, and/or peer tutors. Students progress through the course material at their own pace and may receive one-on-one assistance when they encounter difficulties in learning the material or progressing within the course. In hybrid programs that incorporate traditional lectures and the use of technology, students attend a set amount of lectures per week and then spend time in a computer lab or on their own working with MyLab Math, combining self-paced and guided instruction to complete online assignments and assessments.

While educators who have used each of these implementation approaches have reported success with the use of MyLab in Developmental Math courses, more robust studies, such as one reported later in this document, indicate that these different approaches must be aligned to the specific skill levels and needs of the students.

Product Research

In 2015 using guidance established by the US Department of Education What Works Clearinghouse (What Works Clearinghouse, 2014), Pearson researchers completed a systematic search and review of peer-reviewed studies published since 2008 that assessed the impact of MyLab Math on learner outcomes. From 2008 to 2015, 24 studies on MyLab Math were published in education journals, conference proceedings, or as doctoral dissertations. Among these, two studies (one correlational study and one quasi-experimental study) used rigorous methodologies that provide reliable evidence about the relationship between the use of MyLab Math in Developmental Math Courses and learner outcomes (Krupa, Webel, & McManus, 2015; Tempelaar, Rienties, & Giesbers, 2014)

In 2016, Pearson researchers, in collaboration with faculty at five community colleges in the US, completed a study designed to explore the relationship between the use of MyLab Math and learner outcomes in developmental math courses. The primary aim of this study was to explore whether the use of MyLab Math was a significant predictor of students' probability of passing developmental math courses, after controlling for several other factors that are known to predict student achievement in developmental math.

There are some consistent findings about the impact of MyLab Math in developmental courses emerging from the existing quasi-experimental and high-quality correlational studies. First, across both correlational studies, what is most predictive of learner outcomes (measured by test scores, grades or probability of passing the course) are the scores obtained on MyLab Math homework and quizzes and the mastery of objectives assessed by MyLab Math. In isolation, this is not a surprising finding; however, it validates the correlation between success on MyLab Math and other measures, such as course grades.

Second, the results of the quasi-experimental study show that only students whose scores were at the upper-end of the college admissions test (i.e. the SAT) received higher exam scores in the computer-based course than similar students enrolled in a face-to-face course. This suggests that computer-based instruction that is not accompanied by lectures or more direct, face-to-face contact between learners and instructors may not be sufficient for students who enter college with acceptable, yet minimal, foundational math skills.

Third, findings from both the quasi-experimental and correlational studies suggest that for students enrolled in college level courses and for those enrolled in developmental math courses, the amount of time spent using MyLab Math is not a significant predictor of course grade, scores on the final exam administered outside of the MyLab Math system, or probability of passing the course.

In the following sections we summarize existing studies that have explored the impact of MyLab Math and meet our standards for research quality.

Research Studies Conducted in 2016

A Correlational Study of MyLab Math in Developmental Math Courses

Study Citation	A correlational study of MyLab Math in Developmental Math Courses (2016), Pearson Education, Impact Evaluation - Higher Education Courseware, Efficacy and Research.
Research Study Contributors	Faculty at Robeson Community College, Northwest Shoals Community College, Oakton Community College, Pulaski Tech, and Coppin State University. Christine Leow, Kodi Weatherholtz, Tara Chiatovich, Yun Jin Rho, Carmen Arroyo
Type of Study	Correlational
Sample Size	A total of 862 students from the participating institutions consented to participate in the study and for which data were available for analysis.
Description of Sample	The majority of students in this study were female. Non-white students also made up a majority. Just under half were enrolled at their institution prior to fall 2015, and a similar proportion were registered as full-time students in fall 2015 (see method for more detail on sample). A relatively small percentage of them majored in a STEM field.
Outcomes Measured	The main learner outcomes assessed in this study are whether students completed and passed the developmental math course when using MyLab Math. These outcomes are the common outcomes across the five institutions that allowed for the aggregation of student data for analysis.

Introduction

Researchers on the Pearson Efficacy & Research Impact Evaluation team conducted a study in collaboration with instructors at five institutions where MyLab Math was used in the Fall 2015 Developmental Math course. The goal of this study was to isolate the contribution of MyLab Math to student achievement when other factors, which research has indicated are important predictors of student achievement, are taken into account and are statistically controlled. That is, in this study, we wanted to be able to make valid claims about the strength of the association between use of MyLab Math and student achievement after controlling for confounding variables. Potential confounding factors included in the analysis were: students' enrollment year status (full vs. part-time); years of enrollment in the institution; major; students' race and gender; and the instructional format used in the developmental course.

Method

Multiple procedures were used to collect data on the range of factors known to have a potential influence on student achievement. These included the following: (i) an instructor survey at the end of the semester, (ii) an interview with each course instructor, (iii) course grade data, (iv) course information requested from the instructor at the end of the semester, (v) students' MyLab Math platform data; and (vi) student transcripts requested from the institution.

Despite using a robust data collection strategy, many students were missing one or more of these critical data sources and were excluded from the final analysis. After joining the three sources of student data together (course grades, MyLab Math data, and transcript data) and eliminating students with missing data from any of those sources, this study included a total of 862 participants remaining of the total 1,282 students enrolled in the developmental math courses. This sample represents 67% of the total number of students enrolled in the courses. In addition, since not all instructors participated in the survey, we could not control for instructor variables in the analyses.

Not all forms of problems available in MyLab Math were assigned in all courses, therefore in order to examine the relationship between components of MyLab Math and students' probability of passing the course, separate Hierarchical Generalized Linear Modeling (HGLM) analyses were conducted according to (a) the type of assignment—homework, tests, or quizzes—in MyLab Math and (b) the group of students—those who were newly enrolled in the Fall 2015 semester or those enrolling prior to Fall 2015 (and who may have already completed and failed a previous developmental math course). The analyses were also run using the entire sample of students (not disaggregated by year of enrollment).

Results

The key analyses conducted in this study, regression analysis, adjusted for student background characteristics—including gender and whether students were non-white, enrolled full time, and majored in a STEM field—as well as school characteristics—whether it is in an urban setting and the type of instruction (blended versus emporium) used. Our study showed that:

Number of Attempts Made on MyLab Math Homework Assignments were predictive of all students' probability of passing the course. The more attempts students made in homework, the higher their probability of passing the course. That is, the more students returned to work on homework problems until they got them right, the more likely they were to pass the course. Differences in the probabilities of passing the course were found for students newly enrolled in Fall 2015 and students that had enrolled prior to Fall 2015.

For example, for students newly enrolled in Fall 2015, a typical student's probability of passing the course increased from 9.8% to 53% when they increased their number of homework attempts. However, for students enrolled prior to Fall 2015, the typical student's probability of passing increased only from 72% to 87%. The differences in baseline probabilities between these two groups may be attributed to the fact that 69% of the students who were enrolled at the institutions prior to Fall 2015 had already taken part of the developmental math course sequence or a college-level math course at the institution. Thus in Fall 2015 they began with a greater foundation in math than newly enrolled students.

Scores on the MyLab Math Homework, Quiz, and Test items were predictive of all students' probability of passing the course. The higher the grade a student obtained in homework, quiz, or test assignments, the higher their likelihood of passing the course. This finding is not too surprising as most assignment grades accounted for a portion of the final course grade.

The Mastery of Unique Objectives assessed in MyLab Homework and Quizzes matters for students newly enrolled in Fall 2015 but not for students enrolled prior to Fall 2015. Mastering an objective might not matter for students who had prior college experience or who completed previous developmental math courses where they had already mastered some of the objectives. Specifically, for newly enrolled students with average homework usage, mastering more unique objectives increased the probability of passing the course from 9.8% to 24%. There is no increase in probability of passing the course for a typical student enrolled prior to fall 2015. These possibilities need to be further investigated.

In summary, after controlling for student demographics and institutional characteristics, there are still some aspects of MyLab Math that were found to be significantly related to the probability of passing the course, but for certain characteristics, the findings depended on the type of assignment and on the group of students. Figure X below presents a visual overview of the findings.

***Figure X.* Visual Overview of Findings for Each Type of Assignment, MyLab Math Factor, and Student Group**

		Type of assignment		
MyLab Math Factor	**Student group**	**Homework**	**Tests**	**Quizzes**
Type of Study	all students	↓	⊘	⊘
	enrolled before fall 2015	↓	⊘	⊘
	newly enrolled fall 2015	↓	↑	⊘
Number of attempts	all students	↑	⊘	↑
	enrolled before 2015	↑	⊘	↑
	newly enrolled fall 2015	↑	⊘	↑
Grade	all students	↑	↑	↑
	enrolled before fall 2015	↑	↑	↑
	newly enrolled fall 2015	↑	↑	↑
Number of objectives mastered	all students	↑	⊘	↑
	enrolled before fall 2015	⊘	⊘	⊘
	newly enrolled fall 2015	↑	⊘	↑

↑ **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.**

Discussion

There are some limitations to this study. The research design only allows us to make correlational claims and not causal claims about the impact of use of MyLab Math on students' successful completion of a developmental math course. There were a limited number of meaningful student and institutional variables that we were able to control for, hence, we are not able to rule out all confounding factors that might influence students' achievement in the course. Additionally, due to the unavailability of all types of data for all students, the results discussed may not fully generalize, or apply, to the 1,282 students who were the original focus of the study.

Another limitation is that not all instructors participated in the instructor survey, which would have allowed us to determine which instructor variables may have influenced student achievement in the course. We know instructional design and instructor practices do influence student outcomes and if more student, instructor, and institutional variables could have been included in the analysis, it might give us a fuller picture of the impact of MyLab Math.

Findings from this study point to the need to further examine the different aspects of MyLab Math in more detail. For example, we found that the number of unique objectives mastered matter only in the full sample and not the sample of students who were enrolled prior to fall 2015 and for whom we were able to control for prior achievement. Hence, to further understand how mastery of objectives affects learning, we might want to investigate the different kinds of objectives in MyLab Math and the relation to learning. In addition, replicating the study at other institutions that would involve more students and over more semesters would be needed to allow for further generalization of findings.

It is worth noting is that certain variables —specifically, number of attempts made and unique objectives mastered—were not related to the probability of passing the course for tests, but were related for both homework and quizzes. The research cited above speaks to the benefits of learner support tools offered by MyLab Math, including scaffolding with worked examples (Sharma & Hannafin, 2007) and feedback on performance on assignments (Hattie 2009, 2012). However, homework and quizzes may play a different role than tests in helping students master the material. Thus, future research may want to focus on the contribution of these learner support tools specifically within the framework of homework and quizzes as opposed to tests.

Research Studies Completed Prior to 2016

Undergraduate Students' Knowledge of Algebra: Evaluating the Impact of Computer-Based and Traditional Learning Environments

Study Citation	Krupa, E. E., Webel, C., & McManus, J. (2015). Undergraduate students' knowledge of Algebra: Evaluating the impact of computer-based and traditional learning environments. *PRIMUS*, 25(1), 1330.
Research Study Contributors	Faculty at Montclair State University
Type of Study	Quasi-Experimental Design
Sample Size	123 students
Description of Sample	The students in the study were enrolled in the Intermediate Algebra course at Montclair State University, which is the first course in the credit-bearing mathematics sequence that would prepare students for precalculus. Thus, the sample is limited to students at one university.
Outcomes Measured	The learner outcome assessed was leaners' improved skills in mathematics as measured by the final exam score.

The study explored the impact of two types of instructional settings, face-to-face versus computer-based, on student learning. In the computer-based course, students used MyLab Math.

Method

Participants in the study were students from a mid-sized suburban university on the East coast. Students were enrolled in the Intermediate Algebra course which is the first course in the credit-bearing mathematics sequence and it would prepare students for precalculus.

The study uses a quasi-experimental design. Students enrolling in one of the twelve sections of the course did not know at the time of enrollment which instructional setting they would be in. Half of the courses offered for that semester were given in the computer-based (CB) environment while the other half were in the face-to-face (F2F) environment. Instructors of the F2F courses used E. Martin Gay's Intermediate Algebra *(Sixth Edition)* and could teach the course in any way as long as they covered the required topics. The CB courses were conducted emporium-style (i.e., no lectures) and used the same text along with MyLab Math. Students in the CB course worked through the course content online and were also required to attend normal class hours at the mathematics computer lab on campus, but could proceed through the textbook as they passed quizzes and tests they took in the lab.

A total of 326 students enrolled in one of the 12 sections of the Intermediate Algebra course (134 in CB and 192 in F2F). Of these enrolled students, 123 provided the research team with access to student-level predictors including SAT math scores, high school GPA, Algebra II grade, and college GPA. This study examined the final exam scores, taking into account student-level predictors as covariates, of students (n=73) enrolled in the CB courses compared to students (n=50) enrolled in the F2F courses in Spring 2012.

Results

Use of MyLab Math in a computer-based course that included limited interaction with an instructor was effective for students that entered the course with more than basic math skills, but was not effective for students with lower math skills.
The results of this study suggest that computer-based instruction where no lectures are provided and only limited on-demand assistance is provided may not be sufficient for students who enroll in their first college credit-bearing course with limited math skills (as measured by the SAT). For these students, face-to-face instruction may be needed. However, a fully-computer-based model appears to be effective for students entering college with higher levels of math skills and knowledge.

For students with high prior math ability, use of MyLab Math in a CB environment resulted in higher final exam scores than no use of MyLab Math in a F2F environment. Conversely, students with lower prior math ability achieved higher final exam scores in the F2F environment. Specifically, ANCOVA, with SAT math as the covariate, found that the mode of delivery was significantly related to final exam score ($F=3.58$, $p=0.06$). In addition, ANOVA found that the interaction of mode of delivery and SAT scores was a significant predictor of student achievement ($F=-2.31$, $p=0.029$), indicating that students with higher SAT math scores tended to perform better in the CB setting where MyLab Math was used, while students with lower SAT math scores tended to perform better in the F2F setting.

Discussion

This study is close to a randomized controlled trial because the students had no knowledge of which condition they would be in when enrolling in the course (see above). In addition, prior achievement, as measured by SAT math scores, which normally accounts for a big proportion of the variance in outcomes between groups, was included as a covariate in the analysis.

There are a few caveats associated with the study:

Subset of students with prior achievement data.

The first caveat is that data for only a subset of students out of all students enrolled in the course could be analyzed because only a subset of the students had provided the research team with SAT math scores.

Limited statistical controls.

The second caveat is that only SAT math scores were used as a covariate in the analysis, more covariates could have been controlled for in the analysis to draw a more robust conclusion.

MyLab Math treatment was confounded with type of instruction.

The third caveat is that the treatment was delivered emporium-style while the control had instructors teaching in a traditional way. Thus, results regarding MyLab Math is a combination of MyLab Math, plus emporium style type of instruction. As such, the conclusion for this study is limited to the impact of MyLab Math delivered emporium style.

In conclusion, we can make a causal statement with this study about MyLab Math delivered emporium-style, given the use of an important covariate, prior achievement. However, using additional covariates could make the study more rigorous.

In Search for the Most Informative Data for Feedback Generation: Learning Analytics in a Data-rich Context

Study Citation	Tempelaar, D. T., Rienties, B., & Giesbers, B. (2014). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior,* 47, 157-167.
Research Study Contributors	Faculty at University of Maastricht
Type of Study	Correlation
Sample Size	873 students
Description of Sample	Complete data on 873 out of 922 students in the freshmen cohort enrolled in the quantitative methods course (mathematics and statistics) at the School of Business and Economics at Maastricht University were examined in this study. The sample represents a large diversity of students: only 24% were educated in Dutch high schools, and the largest group (46%), came from the German Abitur system.
Outcomes Measured	The outcomes assessed in this study were learners' completion of the course and achievement as measured by math exam scores and the aggregate scores of three math quizzes.

Introduction

Researchers conducted a study with freshman students enrolled in the quantitative methods course at the School of Business and Economics at Maastricht University in the Netherlands. The course utilized two external e-tutorials: MyLab Statistics and MyLab Math. The results related to MyLab Math are the focus of this report.. Specifically, the authors examined the relationship between the frequency of use (i.e. time spent on MyLab Math task and the number of attempts per MyLab Math task) and students' final exam and quiz scores. The study also determined the relationship between students' performance on the MyLab Math homework and assessments and students' performance on the final exam and quizzes in the course. In addition, the study examined the extent to which alternative data sources, such as learning disposition data, MyLab Math data, and data from final exam and quizzes refer to unique facets of performance, and to what extent the predictions overlap.

Method

Complete data on 873 out of 922 freshmen enrolled in quantitative methods course (mathematics and statistics) at the School of Business and Economics at Maastricht University were analyzed in the study. Student data included demographic data from registration systems, diagnostics entry test data, learning disposition data obtained from surveys, user track data from the learning management system, data from MyLab (i.e. mastery scores, time on task, and number of attempts), and academic performance data (i.e. the final written exam, aggregate scores for three quizzes)

Results

Mastery of the homework and assessments within MyLab Math is predictive of students' performance on the external quizzes and exams administered in the course. However, amount of time and practice (number of attempts) students take to complete items in MyLab Math may be detrimental; more time and more attempts were associated with lower scores on course quizzes and exams. Thus, getting things right in the practice homework and quizzes available in MyLab Math is more important than simply spending lots of time within the computer-based system.

Regression models were used as prediction models. Both performance on the math exam and math quizzes were positively related to mastery of homework and quizzes in MyLab Math (with regression coefficients of .67 and .80 respectively), but they were negatively related to time on task in MyLab Math (with coefficients of .16 and .15 respectively) and average number of attempts in MyLab Math (with coefficients of .32 and .15 respectively), when all of these MyLab Math variables were simultaneously considered.

Discussion

This study showed a positive association between MyLab Math mastery and performance on the final math exam as well as the aggregate of three quizzes. This association is between two independent variables after controlling for time spent on task in MyLab Math and the average number of attempts in MyLab Math.

A **caveat** of this study is that it did not account for other confounding factors in explaining the association between MyLab Math mastery and academic performance.

In conclusion, this study does not allow us to make any causal statements. Instead, it only shows the relationship between MyLab Math mastery and academic performance after controlling for time on task in MyLab Math and the average number of attempts made in MyLab Math.

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