THE UNIVERSITY OF UTAH
UTAH EDUCATION POLICY CENTER

Impact of K-12 Math Personalized Learning Software on Student Achievement

June 2020

THE UNIVERSITY OF UTAH

UTAH EDUCATION POLICY CENTER

Bridging Research, Policy, & Practice

The Utah Education Policy Center (UEPC) is a an independent, non-partisan, not-for-profit research-based center at the University of Utah founded in the Department of Educational Leadership and Policy in 1990 and administered through the College of Education since 2007. The UEPC mission is to bridge research, policy, and practice in public schools and higher education to increase educational equity, excellence, access, and opportunities for all children and adults.

The UEPC informs, influences, and improves the quality of educational policies, practices, and leadership through research, evaluation, and technical assistance. Through our research, evaluation, and technical assistance, we are committed to supporting the understanding of whether educational policies, programs, and practices are being implemented as intended, whether they are effective and impactful, and how they may be improved and scaled-up, and become sustainable.

Please visit our website for more information about the UEPC.

http://uepc.utah.edu

Andrea K. Rorrer, Ph.D., Director
Phone: 801-581-4207
andrea.rorrer@utah.edu

Cori Groth, Ph.D., Associate Director
Phone: 801-581-4207
cori.groth@utah.edu

Citation: Owens, R., Rorrer, A., Ni, Y., Onuma, F., Pecsok, M., & Moore, B. (2020). Longitudinal Evaluation of the Math Personalized Learning Software Grant Program. Salt Lake City, UT: Utah Education Policy Center.

Table of Contents

List of Figures

List of Tables

Introduction

Purpose of this Evaluation

In 2016, the Utah Science Technology Engineering and Mathematics Action Center (STEM AC) contracted with the UEPC to conduct a five-year evaluation of the Math Personalized Learning Software Grant. Evaluation results of Year 1 (2016-2017) and Year 2 (2017-2018) indicate that:

- Users had greater improvement in raw scores (compared to the previous year) than non-users.
- Of students who were proficient the year prior to the evaluation, software users were less likely to be not proficient in the year of the evaluation compared to other students.
- Of students who were not proficient the year prior to the evaluation, software users were more likely to be proficient the year of the evaluation compared to other students.
- Software users also had higher average student growth percentiles (SGPs) compared to other students.
- Higher levels of use were associated with better performance for most software vendors.

The positive findings reported in the Year 1 Report (*STEM Action Center Program Evaluation, 2016-17), and Year 2 Report (Utah STEM Action Center Program Evaluation, 2017-18)* were consistent with national research on the impact of math learning software on student achievement. For example, meta-analyses have found effect sizes for use of math software ranging from -.11 to 1.02, with the majority of studies yielding a small to moderate positive effect on math performance (Cheung & Slavin, 2013; Young, Gorumek, & Hamilton, 2018). Thus, to extend the analyses conducted in the past two annual evaluations, this year wwe examine the use and effectiveness of personalized learning math software to increase student achievement longitudinally. The personalized learning math software evaluated here was provided to Utah public schools through grant funds administered by the Utah STEM Action Center.

Longitudinal research is important because it allows us to understand the changes that occur over time and determine whether or not there is value in the persistence of implementation or use. Previous evaluation reports analyzed data and reported results for a single year. This year's evaluation is also a departure from previous evaluations in that we utilize propensity score matching to construct a more meaningful comparison group. Using propensity score matching for this evaluation permits us to compare software users to non-users in similar schools (e.g., schools similar in terms of race and ethnicity, regional variation, and rates of mobile student, chronically absent students, and students who qualify for free and reduced lunch). Use of propensity score matching in our analyses reduced bias by eliminating differences between the digital math software users and comparison groups in terms of demographic and other characteristics such as qualifying for free and reduced lunch, student mobility, and chronic absence. Previous evaluations compared software users to all other students.

Evaluation Questions

To understand the impact of use of the K-12 Personalized Learning Software, the UEPC examined the following evaluation questions:

User and Non-User Comparisons

1. How do digital math users differ from non-users in terms of demographic characteristics?
2. How do digital math users vary across vendors?
3. How do students use math software?

Software Use and Math Performance

1. Do software users perform better than non-users?
2. What student/school characteristics are related to performance?
3. How does the way students use math software relate to performance?

K-12 Math Personalized Learning Software Grant Overview

In 2013, the Utah Legislature passed House Bill 139[1] (HB 139) which created the STEM AC. The primary goal of the STEM AC, as stated in the legislation, is to provide STEM education and digital learning tools to support teacher professional development and get students excited about STEM. The bill also created the STEM education related technology program which involves the STEM AC acting as a research and development center for education related instructional technology. In 2014, the Legislature passed House Bill 150[2] which expanded the scope of the STEM education related technology program and provided ongoing appropriation for the STEM AC from the general fund.

A major component of the STEM education related technology program is the K-12 Math Personalized Learning Software Grant. The K-12 Math Personalized Learning Software Grant provides Utah schools with access to approved math software programs intended to improve student performance in mathematics. School districts or charter schools apply to STEM AC for grant funds to pay for licenses so students and educators can access math software from vendors on the approved list.

Program Purpose

The purpose of the K-12 Math Personalized Learning Software Grant is to provide students access to math software to improve student outcomes and math literacy[3]. The personalized math software programs are intended to improve student math performance by increasing student awareness, engagement, interest, and perceived utility of math. In addition, an

---

[1] https://le.utah.gov/~2013/bills/static/HB0139.html

[2] https://le.utah.gov/~2014/bills/static/HB0150.html

[3] K-12 Math Personalized Learning Software Grant, https://stem.utah.gov/grants/k-12-math-personalized-learning-software-grant/

intended outcome is improved performance on standardized math tests, which is outcome focus of this evaluation.

Criteria for Math Software Vendor Selection in Grant Program

In order to be included as an approved K-12 Math Personalized Learning Software provider, software vendors must meet the minimum criteria, as defined by the STEM-AC. First, vendors may offer licenses to schools for a trial use, or pilot program. As part of the mandatory criteria for consideration to be added to the STEM AC K-12 Math Personalized Learning Software Provider List, [4] the math software program must:

- Assess student ability.
- Have content that is tailored to individual students, including remediation and enrichment.
- Align with state core standards for mathematics.
- Provide performance data to parents and teachers.
- Provide for teacher customization of material or allow teachers to assign specific activities or problems.
- Receive positive responses from teachers and students on end of year surveys.

In addition, the Math Software Vendor must:

- Provide teachers and administrators with professional development and technical support in use of software.
- Demonstrate that the software is research-based and has been successfully implemented in the state.
- Provide usage data to the external evaluator, the Utah Education Policy Center (UEPC), and participate in evaluations.

The K-12 Math Personalized Learning Software Grant also requires vendors to provide support for effective in-class and at-home use of software. Vendors provide implementation guidelines, teacher training and presentations, and are available for technical assistance.

Target Population and Audiences

The Math Personalized Learning Software Grant is designed to support Utah public school students in kindergarten through twelfth grade. Districts and schools may choose to participate in the grant program. The analyses in this evaluation include scores from students in third grade and above on the Student Assessment of Growth and Excellence (SAGE) math test, which was Utah's previous state mathematics assessment prior to 2019. This evaluation report is provided to guide program improvement efforts for the Math Personalized Learning Software Grant supported by the STEM AC.

[4] Utah STEM Action Center, *Request for Statement of Qualifications and Approved Vendor List for K-12 Mathematical Personalized Learning Software* (n.d.).

Review of Literature

Educational Technology in the 21st Century

The 21st century has seen increasing integration of technology into aspects of professional and personal life. Prominence of the role of technology in education has also increased. Demand for and use of technology in education has steadily increased (Blazer, 2008). Technology use and integration has increased in many classrooms world-wide. One survey found that 48% of classrooms worldwide utilize desktop computers in lessons (Cambridge Assessment International Education, 2018). In addition, 42% of classrooms world-wide use smartphones, 33% use smartboards, and 20% use tablets. Results of the same survey suggest technology use in the United States is greater, with 75% of classrooms utilizing desktop computers, 74% using smartphones (Cambridge Assessment International). Increased interest in technology can be seen in programs promoting one-to-one device adoption, in which each student is provided a device for personal use and may include access to specific educational software (Franklin, Orians, & Rorrer, 2016).

A review of literature on educational technology demonstrates many potential benefits of technology in teaching and learning (Franklin, Orians, & Rorrer, 2016; Blazer, 2008; IFC Consulting Services Ltd, 2015). Some potential benefits of technology for learning include the ability to accommodate for individual students learning pace and style, and increased access to educational material (Blazer, Bonifaz & Zucker, 2004). In addition, technology may provide students with technological skills necessary for future employment, develop critical thinking, problem-solving, and communication skills, and provide students with opportunities to collaborate with peers and engage in hands-on activities and the benefit of immediate feedback (Blazer, Jobe & Peck, 2008; Bebell, 2005). Furthermore, educational technology has the potential to benefit teaching in similar ways. Technology can enhance teacher ability to differentiate content and assessments to meet students' individual needs and provide access to additional materials and content for lessons (Blazer; Dunleavy et al., 2007; Waddoups, 2004). Technology can also improve communication with and engagement of parents in their child's learning. Educational technology can also result in increased efficiency and cost savings (IFC Consulting Services Ltd).

Despite the rhetoric touting the many benefits of technology in education, the way technology is implemented in classrooms is important and challenging (Franklin, Orians, & Rorrer, 2016). A number of strategies have been identified that contribute to success of educational technology. Some strategies to improve success of technology include planning and involving teachers in planning (Blazer, 2008; Franklin, Orians & Rorrer), providing students and teachers access to necessary tools, and providing access equitably to all students (Blazer). In addition, technology must be appropriately integrated into curriculum rather than treated as a supplement or separate subject. Strong leadership (Blazer) and teacher training and professional learning, as well as provision of technical support to teachers are also important to success of educational technology (Blazer; Franklin, Orians, & Rorrer). Finally, educational technology is more likely to be successful when parents and community stakeholders are informed and engaged, and when the implementation and outcomes of education technology are evaluated (Blazer).

When educational technology is used effectively student achievement increases (IFC Consulting Services Ltd, 2015). The focus of the present evaluation is the use of a specific kind of educational technology, personalized math learning software. Next, we provide a review of literature specific to educational technology and related outcomes, including mathematics achievement.

Educational Technology and Student Achievement in Mathematics

Many schools utilize digital technologies for instruction and learning (Hardman, 2019). A substantial amount of literature has been devoted to assessing the effectiveness of technology in enhancing math education, and many studies have demonstrated positive effects (Murphy, 2016; Cheung & Slavin, 2013; Young, Gorumek, & Hamilton, 2018). To date, research in this area has indicated that technology in education can have positive effects such as increased engagement and motivation, improved student-teacher interaction, and increased student collaboration. Technology can also increase students' comfort with learning math and their understanding of math concepts (Murphy, 2016).

The success of mathematics technology in raising student achievement is dependent on how well technology is integrated with curriculum. Yet, the challenge of curriculum integration is among the most widely cited in literature on education technology (Franklin, Orians, & Rorrer, 2016). The Substitution, Augmentation, Modification, and Redefinition (SAMR) model created by Puentedura (2013) and the Technological Pedagogical and Content Knowledge (TPACK) framework, developed by Mishra and Koehler (2006) provide useful perspectives for the integration of technology and curriculum.

Puentedura developed the SAMR model, which provides a framework for understanding how technology is integrated into teaching and learning. The SAMR model categorizes technology into four degrees of integration, substitution, augmentation, modification, and transformation. Puentedura (2013) labels the lower degrees, substitution and augmentation, as enhancement and labels the higher degrees, modification and redefinition, as transformation. Bray and Tangney (2017) reviewed 139 studies of technology use in mathematics education and classified them into the appropriate SAMR degree. They found that over 60% of studies employed technology at the augmentation level. Instructional videos are an example of augmentation, because they provide information like a teacher would, but are augmented with the ability to view them outside of class time and to pause and rewind. Bray and Tangney concluded that technology is predominantly used to enhance teaching and the potential of math technology to transform student learning experience is yet to be realized.

Mishra and Koehler (2006) expanded the Pedagogical Content Knowledge (PCK) framework proposed by Shulman (1986) to include Technology. Teaching, according to the PCK framework, involves the continuous interaction of content knowledge, curriculum knowledge, and pedagogical knowledge. Mishra and Koehler recognized that technology was introduced into educational settings with insufficient attention to how it would be used. In the TPACK framework, Mishra and Koehler sought to create a framework to provide a coherent way of thinking about technology integration and to transform teacher education and training. The TPACK framework emphasizes the importance of content knowledge (e.g. knowledge about mathematics), pedagogical knowledge (e.g. knowledge of instructional strategies and epistemologies), and technological knowledge (e.g. knowledge of the internet or specific apps and programs). The framework depicts these knowledge areas as three intersecting circles, emphasizing the overlap between the three knowledge areas and the notion that any of the three knowledge areas should not be considered independent of the context of the other knowledge areas (Mishra & Koehler, 2006).

Koh, Chai, and Lim (2017) assessed outcomes of a TPACK-based year-long professional development effort to increase integration of technology in elementary school teachers. In teams, teachers assessed existing lesson plans using a TPACK-21st Century Learning rubric, set goals to improve lesson plans, redesigned lesson plans, then implemented, evaluated, and reflected on the process and outcomes. Koh and colleagues found that on pre and post surveys, teachers' confidence in several knowledge domains increased, and based on observations, teacher integration of technology had improved.

Technology use in education is widespread, and has many benefits for teaching and learning, particularly when used effectively. The SAMR model and the TPACK Framework illustrate the complexity and importance of integrating and quality implementation of technology in education. The focus of the current evaluation is outcomes of students who participate in the digital math software program. Although a complete understanding of student outcomes cannot be achieved without an understanding of teacher practices and integration of math software, this report only address outcomes of student use. These important issues will be addressed in future reports utilizing additional data sources.

Report Organization

The remainder of this evaluation report is divided into four sections, as outlined below:

- **Brief Methodology.** We describe the design of the evaluation including samples and analyses. The method section also includes an explanation of the two sources of data used for the evaluation, and information about data use.
- **Digital Math Software User and Non-User Information.** In this section, we present findings on student characteristics of digital math software users and non-users as well as student characteristics of users compared across vendors. Student characteristics considered include race or ethnicity, rural status, gender, income, mobility, chronic absence, and grade level. In this section we also present information about student use, including overall use and consistency of use.
- **Digital Math Software Use Information.** This section provides information about how much students used software and information about how consistently students used software. Use and consistency of use are reported for each software vendor.
- **Digital Math Software Users and Non-Users Math Performance.** Findings in this section include average math performance indicators for users and non-users. We also present generalized estimating equations (GEE) regression model results demonstrating how software use is related to performance on the math SAGE test for all users and by vendor.
- **Student and School Characteristics and Performance.** In this section, we present regression results showing the relation of student and school characteristics to math

performance. Finally, we include GEE results of overall use, years of use, and consistency of use.

- **Amount and Consistency of Digital Math Software Use and Performance.** In the final section of the report, we examine how students use digital math software is related to SAGE performance. We include regression results showing how amount of use measured by use quartile, years of use, and consistency of use are related to performance for digital math software users. Note that non-users were not included in the models reported in this section of the report.
- **Summary of Findings.** We provide a summary of the highlights of each aspect of the analyses. Following the summary of findings, we discuss questions that have yet to be addressed by the larger evaluation. We also present possible future directions for evaluation activities.
- **Considerations for Improving the K-12 Math Personalized Learning Software Grant.** Finally, we conclude the report with recommendation for the K-12 Math Personalized Learning Software Grant program implementation and improvement.

Methodology Overview

In this section, we briefly describe the data sources, samples, statistical analyses, and outcome indicators used in this evaluation. For detailed information about our methodology see Appendix A. Methodology

Data Sources

Only three software vendors provided multiple years of student usage data to the UEPC for analyses. Table 1 shows the years of data provided by the vendors who provided sufficient data.

Table 1. Vendors Included and Years of Data Provided

Vendor	Years of Data
ALEKS	2016-2018
i-Ready	2017-2018
ST Math	2015-2018

Two additional vendors, Mathspace and Imagine Math were not included in this evaluation. Mathspace had not been part of the STEM AC K-12 Math Personalized Learning Software Grant long enough to have sufficient data for inclusion. Imagine Math had incomplete data, which were not sufficient for inclusion in the longitudinal study.

Outcome data for this study were accessible for use in this evaluation through a data sharing agreement between the Utah State Board of Education (USBE) and the UEPC.[5] Student outcomes included SAGE mathematics proficiency, standardized scores, and student growth percentile (SGP). We also used demographic variables for propensity score matching and to control for pre-existing differences between students, including student gender, race and ethnicity, qualification for free and reduced lunch, mobility status, regional status, and chronic absence. For inclusion in this study, we calculated school-level percentages of qualification for free and reduced lunch, mobility status, and chronic absence.

Samples

The primary sample for this evaluation consists of 155,866 Utah public school students who used at least one of the STEM-AC approved Math Personalized Learning Software Grant software programs one or more years from 2015-2018. SAGE math tests were offered for Grades 3 and above. Thus, the sample does not include data from students in kindergarten through second grade. For students whose data were provided by vendors and who completed a SAGE math test (n=127,571), most of the students (n=81,996) had only one year of data available, which means these students were included in user data of one of the software vendors during only one academic year. Some students (n=36,729) appeared in vendor data for two years. Thus,

[5] The views expressed in this report are those of the authors and are not necessarily the USBE's or endorsed by the USBE.

two years of data were available. For 7% of the sample (n=8,846), three or four years of data were available. We excluded vendor data if we were unable to match USBE records. Establishing parameters for usable data sets, records that had excessively high time usage data (e.g. about 14 hours a week) were excluded as these students were extreme outliers with much higher usage than other students. A data set for analysis was created using the following criteria: vendor login and school year information, name, school and school year matching algorithm.

We compared digital math software users to non-users. Non-users are defined as students who did not use any of the math software programs funded by the STEM AC. We had no way of verifying whether these students used other math software, but they were not matched to use data from any of the STEM AC funded software providers. Throughout this report and consistent with previous evaluation reports, non-users refers to students who did not use STEM AC funded software.

For descriptive comparisons, we report on a larger sample of all digital math software users in grades 3-12 (n=155,866) and a comparison group of all non-users in grades 3-12 from USBE data (n=442,994). Students were included in the larger sample for descriptive comparisons even if they did not have SAGE math scores. The longitudinal analyses included only students in grades 3-12 who completed one or more SAGE math test during 2015-2018, including digital math software users (n=127,571) and a comparison group that comprised a subset of non-users (n=223,878). We selected the comparison group using propensity score matching. This statistical matching technique permitted the selection of non-users from schools who matched user schools in terms of race, mobility status, rural status, testing below grade level, chronic absenteeism, and gender. The propensity score matched sample consisted of 223,878 students and provided a more appropriate comparison group than all non-users. The sample included:

1. Software users matched to USBE records (n=155,866)
    - Software users with SAGE scores (n=127,571)
2. All non-users (n=442,994)
    - Propensity Score Matched non-users with SAGE scores (n=223,878)

Statistical Analyses

The following statistical methods were used in analyses reported in this evaluation:

1. Frequencies of student characteristics were reported for digital math users and non-users for race and ethnicity, rural status, gender, whether students qualify for free or reduced lunch, mobility status, and chronic absence. Due to the longitudinal nature of the data, we do not report on grade level of students, because students who used digital math software multiple years have multiple grade levels. Grade level was not used as a control variable in longitudinal regression models.

2. We divided digital math software users within vendors into quartiles based on the average amount of time they spent using digital math software each month of use. Within each vender, each quartile contains 25% of users of that vendor's software. Quartile 1 contains the users with the lowest averages. Quartile 2 contains the users

with the second lowest averages. Quartile 3 contains users with the second highest averages. Quartile 4 contains users with the highest averages. Note that quartiles were repeated measures. Each student was assigned a quartile for each year the student used digital math software.

3. For each user with more than one month of data, we reported the coefficient of variation (COV) as an indicator of consistency of use. The COV is calculated using the mean and standard deviation of minutes of use per month according to the following formula:

$$C_v = \frac{\sigma_{Period\ Usage}}{\mu_{Period\ Usage}}$$

   Note that a high COV indicates less consistent use, and a low COV indicates more consistent use. We reported average COV for each vendor for each use quartile. COV, like quartile, was calculated for each year a student used digital math software.

4. For longitudinal analyses we used the Generalized Estimation Equation (GEE), with linear and logistic regression. GEE, in interpretation, is similar to generalized linear models. Unlike generalized linear models, GEE accommodates for repeated measures or year over year data for individuals. Because our data are longitudinal, we want to include multiple years of data for individuals. In the general linear model, including repeated measures on individuals violates the assumption of independence, or the assumption that outcomes of individuals do not influence other outcomes. A students' SAGE math scores are highly related and not independent of their SAGE math scores from previous years. By using GEE, we are able to use SAGE scores from the same students from multiple years as outcomes, providing a more comprehensive and accurate view of the true effects of digital math software use.

   We used two sets of models. The first set of models included digital software users and propensity-score matched non-users. The second set of models included only digital math software users. Each set of models included 12 models, one for each of the three outcome indicators for all digital math software users and one for each of the three software vendors. Variables included in the models are shown in Table 2.

Table 2. Variables Used in GEE Regression Models

Student Characteristics	School Characteristics	Use Variables (user only models)
Gender	Proportion of Low Income	Years of Use
Race or Ethnicity	Proportion of Mobile	Use Quartiles
Qualify for Free and Reduced Lunch	Proportion of Chronic Absence	Consistency of Use
Mobility Status		
Rural Status		
Chronic Absence Status		

Outcome Indicators

For longitudinal models outcomes, our primary outcome of interest was performance on Student Assessment of Growth and Excellence (SAGE) Math tests for each year of student data. We used three related but distinct indicators calculated from SAGE scores:

1. Proficiency
2. Percentile rank estimated from standardized scores
3. SGP

These outcomes capture the variance in performance.

Proficiency

Proficiency on SAGE shows how participants scored relative to a pre-defined benchmark. More than 200 educators, education experts, and other stakeholders participated in a week long workshop on standard setting to determine proficiency levels.[6] The outcome we use for proficiency is the dichotomous proficient (1) or not proficient (0). However, for average proficiency, we reported the levels of proficiency provided by the USBE as: Below Proficiency, Approaching Proficiency, Proficient, and Highly Proficient. Based on guidelines for interpreting SAGE scores,[6] a score of proficient or highly proficient indicates a student is on track in terms of college and career readiness. A score below proficient or approaching proficient indicates a student is not on track in terms of college and career readiness.

Percentile Rank

We calculated standardized scores from student math SAGE scores. Standardized scores tell us how well a student performed on a test in units of standard deviations from the mean score. An advantage to using standardized scores is that we can compare all students regardless of which grade level SAGE math test they completed. A disadvantage to using standard scores is that they are not easy to interpret. To make results easier to interpret, we converted standardized scores into percentile ranks.

The percentile rank allows us to know how students performed relative to other students who took the same test. The higher the percentile rank, the better the student performed. For example, a student who took the 8^{th} grade math test and scored in the 56^{th} percentile performed better than 56% of other students who took the 8^{th} grade math test.

Student Growth Percentile (SGP)

SGP shows student growth or improvement from the previous year SAGE math score relative to similar students. SGP takes into account performance and past performance. A student with an SGP of 52% showed more growth than 52% of other students who performed similar to them in the past.

[6] https://www.uintahonline.com/uploads/2/3/1/0/23109436/overviewof_whatissage.pdf

Digital Math Software User and Non-User Information

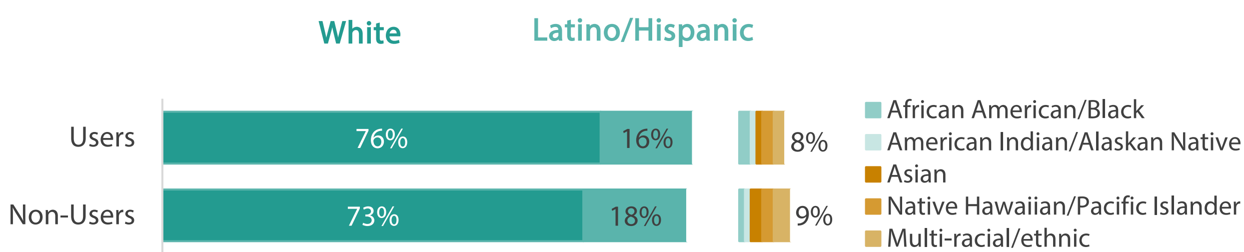
This section of the report provides descriptive information about all users and non-users. The sample used for descriptive analyses includes software users and non-users statewide in grades 3-12. The sample in later sections is limited to software users with SAGE math test scores and propensity score matched non-users, but this section describes all software users and non-users in grades 3-12 statewide.

How do Digital Math Software Users Differ from Non-Users in Terms of Demographic Characteristics?

Using descriptive statistics, this section examines the demographic attributes of digital math software users and non-users. Digital math software users and non-users are disaggregated by race and ethnicity, rurality, gender, eligibility for free or reduced lunch, mobility, and chronic absenteeism status. The software user and the non-user group consisted of students in grades 3-12. We do not report frequencies of students by grade level, because multiple years of data are included for many students, meaning that many students have multiple grade levels. This section reports on all digital math software users and all non-users.

Findings

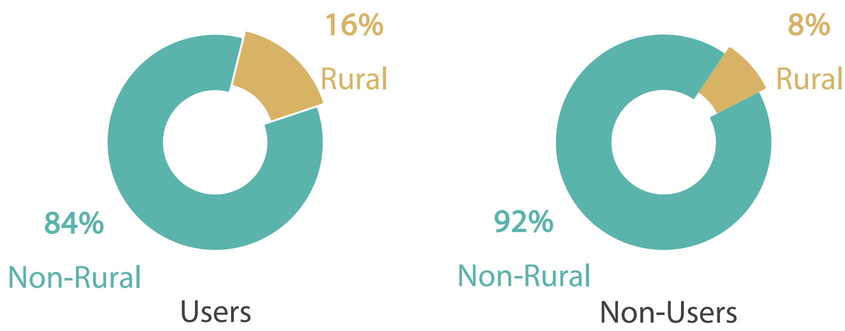
Figure 1. Race and Ethnicity of Software Users and Non-Users



Data sources: USBE and Digital Math Software Vendors

USBE reports students in the following race and ethnicity categories—White, Black or African American, Asian, American Indian and Alaskan Native, Native Hawaiian and Pacific Islander, or multiple races. Additionally, USBE determines ethnicity by whether a student is of Hispanic origin or not. This study utilized the same categories for race and ethnicity as USBE. As depicted in Figure 1 above, White students accounted for the largest share of digital math software users (76%) and non-users (73%) as compared to their representation of 74% among students in the schools included in this study. Additionally, students of color, which included students identified as African American/Black, American Indian/Alaskan Native, Asian, Hispanic/Latino, Multi-race/ethnicity, and Native Hawaiian/Pacific Islander, accounted for a lesser fraction of users and non-users of digital math software than their representation in the general student population. Moreover, these students are more represented among non-users of digital math software (27%) than users (24%), and collectively account for 26% of students in the schools included in the study.

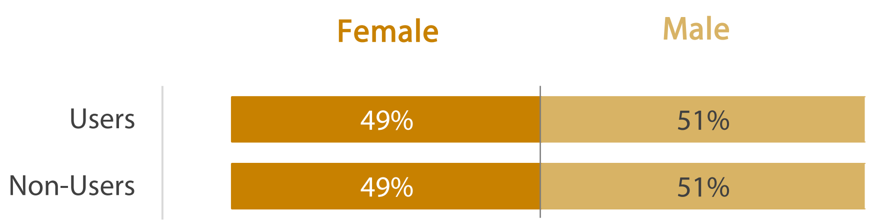
Figure 2. Rural and Non-Rural Software Users and Non-Users



Data sources: USBE and Digital Math Software Vendors

Students were also identified by USBE according to their school's locale, which includes four designations—rural, city, suburb, or town. Students whose schools were designated as rural were categorized as rural in the current report. Additionally, students whose schools were described as located in a city, suburb, or town were categorized in this report as non-rural. Findings shown in Figure 2 suggest that non-rural students comprised the majority of digital math software users (84%) and non-users (92%), while rural students were in the minority in both populations (16% and 8%). Rural students, however, were slightly overrepresented among digital math software users (16%) in view of their 10% representation among students in the schools included in this study.

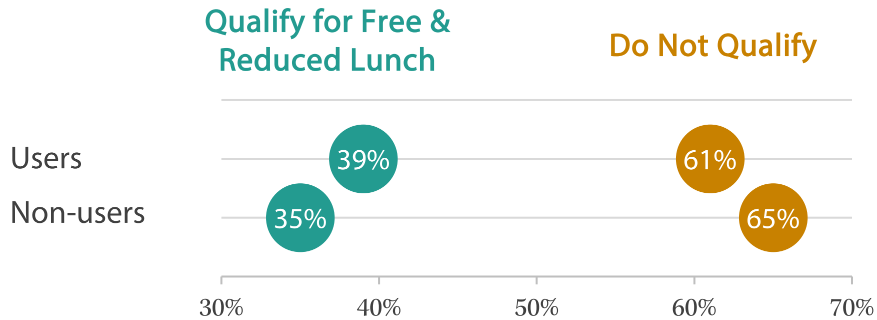
Figure 3. Gender of Software Users and Non-Users



Data sources: USBE and Digital Math Software Vendors

In the current report, we defined gender, similarly to USBE, as including two categories—male and female. As illustrated in Figure 3, female and male students are near evenly represented among digital math software users and non-users. Among digital math software users, female students accounted for 49% of students, while male students accounted for 51%. The same gender breakdown also held for non-users of digital math software and the larger sample from which both digital math software users and non-users were drawn.

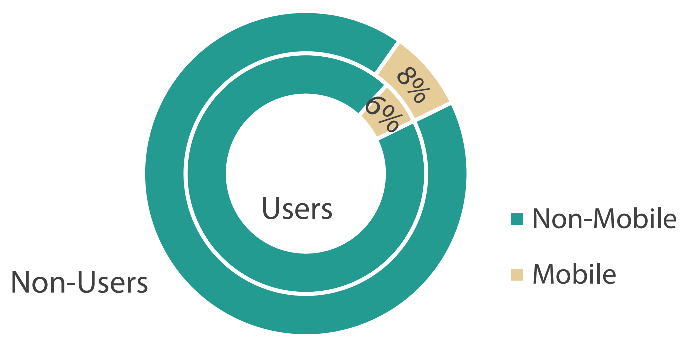
Figure 4. Digital Math Software Users and Non-Users and Whether they Qualify for Free and Reduced Lunch



Data sources: USBE and Digital Math Software Vendors

Economically disadvantaged status, according to USBE, is determined by whether or not a student qualifies for free or reduced lunch. In the current report, rather than using the term economically disadvantaged, we report on students who qualified for or were eligible for free and reduced lunch. As Figure 4 depicts, 39% of students who use digital math software were eligible for free or reduced lunch, as compared to 35% of non-users. Students eligible for free or reduced lunch accounted for 36% of students in the schools included in the study, a slightly lower percent than among digital math software users.

Figure 5. Mobility of Software Users and Non-Users

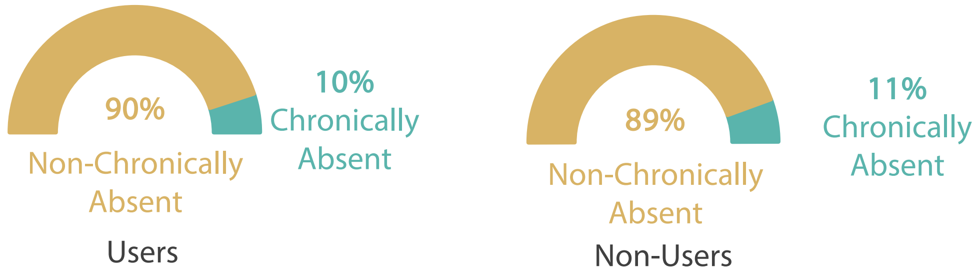


Data sources: USBE and Digital Math Software Vendors

Consistent with USBE's use of mobility, this evaluation determined student mobility by whether a student was enrolled in a particular school for the entire school year. Thus, we classified a student as mobile, if the student attended more than one school in a given school year, or non-mobile if they attended only one school in a given school year. According to Figure 5, non-mobile students comprised the majority of digital math software users (94%) and non-users (92%). Mobile students, while accounting for a lesser percentage of both populations, were slightly more represented among non-users (8%) of digital math software than users (6%).

Among students in the school included in this study, 7% were identified as mobile, and 93% were identified as non-mobile.

Figure 6. Chronic Absence of Software Users and Non-Users



Data sources: USBE and Digital Math Software Vendors

Figure 6 provides digital math software users and non-users disaggregated by chronic absenteeism status. Consistent with the USBE definition, we determined chronic absenteeism status by whether a student was absent for 10% or more of their total membership days in the school in which they had the highest number of attendance days. Among students in the schools included in the study, 11% were classified as chronically absent as compared to 10% of digital math software users and 11% of non-users. Additionally, most digital math software users (90%) and non-users (89%) were non-chronically absent students.

Summary

In summary, the sample from which digital math software users and non-users were drawn was composed, primarily, of White students, male students, students who not eligible for free and reduced lunch, non-mobile students, non-rural students, and non-chronically absent students. As the figures above illustrate, the compositions of the digital math software user and non-user populations were very similar to that of the overall student sample. The largest differences between digital math software users and non-users and the overall student sample were shown in Figure 2, which demonstrates rural students were slightly overrepresented among digital math software users, and in Figure 4, which shows students eligible for free or reduced lunch were slightly overrepresented among digital math software users.

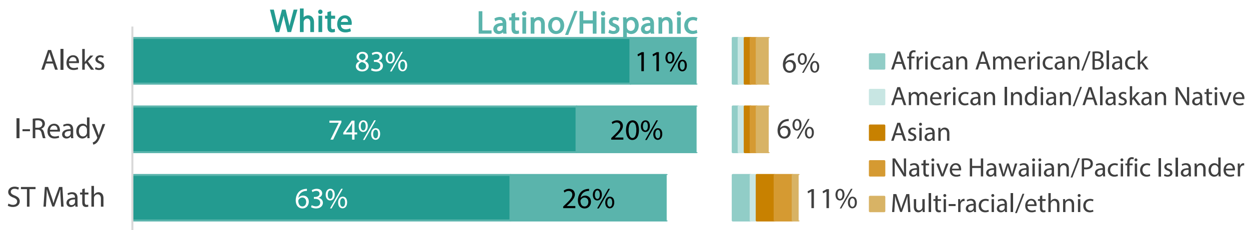
How do Digital Math Users Vary Across Software Vendors?

This section extends the prior section's findings on the demographic characteristics of digital math software users by further disaggregating these students based on the type of digital math software they utilized. ALEKS, i-Ready, and ST Math users are the focus of this section. These three groups of digital math software users, as in the prior section, are differentiated by race and ethnicity, regional locale, gender, eligibility for free or reduced lunch, mobility, and chronic absence. Just as with our description of all users and non-users, we do not report counts of student grade level in our comparison of software vendor users, because students with multiple years of data have multiple grade levels. ALEKS software users included students in grades 3-

12. i-Ready software users included students in grades 3-8. ST Math software users were in grades 3-9.

Findings

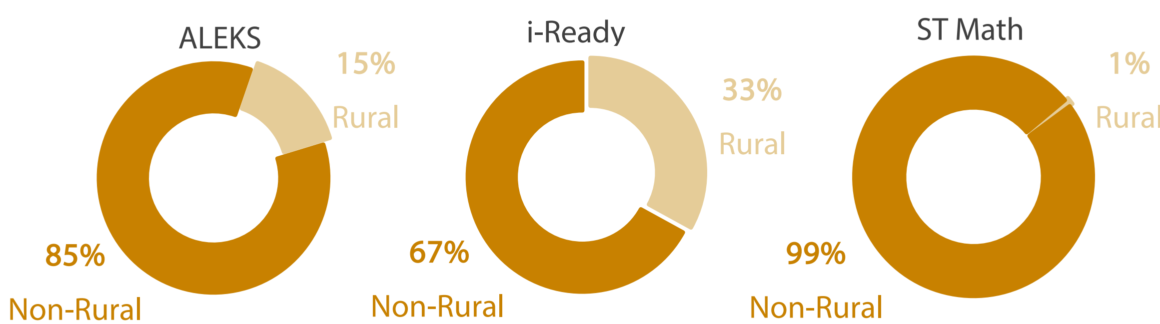
Figure 7. Race and Ethnicity of Software Users in Each Vendor



DATA SOURCES: USBE AND DIGITAL MATH SOFTWARE VENDORS

The student sample in the current study was 74% White, 2% Black or African American, 2% Asian, 1% American Indian and Alaskan Native, 2% Native Hawaiian and Pacific Islander, and 3% multiple races. As Figure 7 indicates, the vast majority of digital math software users, irrespective of vendor, were White students. ALEKS and i-Ready, however, had a higher percentage of White users (83% and 74%) than ST Math (63%). Latino/Hispanic students were the second most represented group of users across the three Digital Math Software Vendors, accounting for 26% of ST Math users, 20% of i-Ready users, and 11% of ALEKS users. Additionally, students of color, were most represented among ST Math users (37%), followed by i-Ready (26%), and lastly ALEKS (17%).

Figure 8. Rural Status of Software Users in Each Vendor



Data sources: USBE and Digital Math Software Vendors

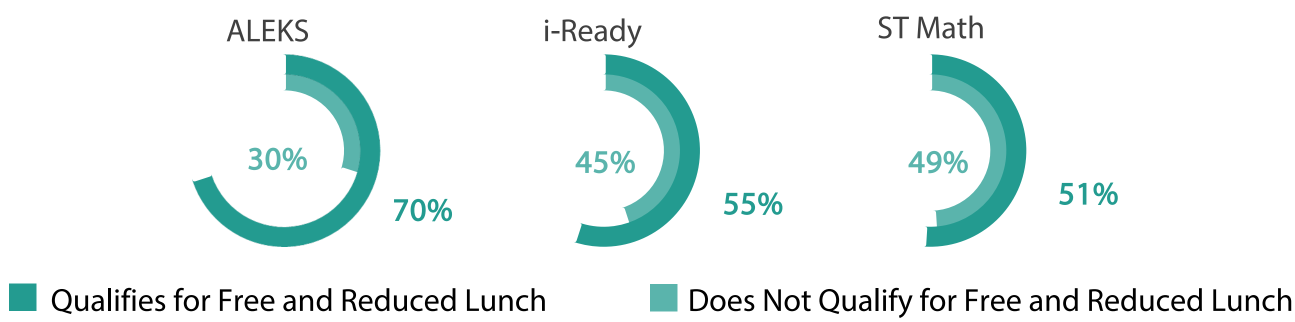
As seen in Figure 8, rural and non-rural students accounted for 10% and 90% of students, respectively, in the schools included in this study. As Figure 810 illustrates, most users of ALEKS (85%), i-Ready (67%), and ST Math (99%) were non-rural students. Rural students accounted for a lesser percentage of users across vendors. However, these students are more represented among i-Ready users (33%) than ALEKS (15%) and ST Math (1%).

Figure 9. Gender of Software Users in Each Vendor

Data sources: USBE and Digital Math Software Vendors

When disaggregated by gender, students in the schools included in this study were 49% female and 51% male. As Figure 9 depicts, ALEKS users were evenly distributed by gender. Among ST Math and i-Ready users, however, male students (53% and 52%) were slightly more represented than female students (47% and 48%).

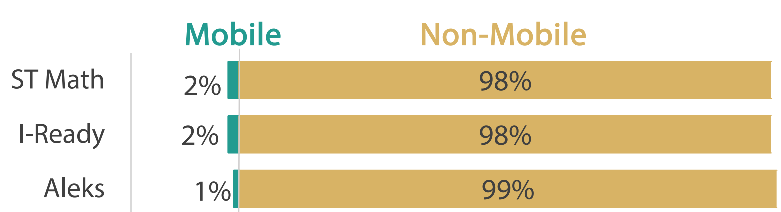
Figure 10. Student who Qualify for Free and Reduced Lunch in Each Software Vendor



Data sources: USBE and Digital Math Software Vendors

Students eligible for free and reduced lunch comprised 36% of the student sample in this study, and those who did not qualify for free and reduced lunch accounted for 64% of students. As Figure 10 depicts, students who were not eligible for free and reduced lunch accounted for more than half of ALEKS (70%), i-Ready (55%), and ST Math (51%) users, and were most represented among ALEKS users. Students who were eligible for free and reduced lunch, on the other hand, are most represented among ST Math users, at 49%, and least represented among ALEKS users, at 30%.

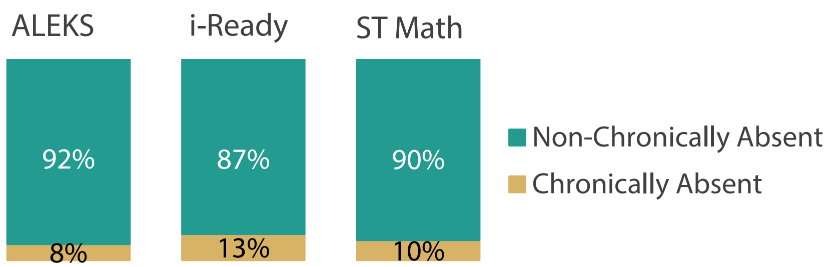
Figure 11. Mobility Status of Software Users in Each Vendor



Data sources: USBE and Digital Math Software Vendors

As seen in Figure 5, mobile students accounted for 7% of students in the schools included in this study. Findings shown in Figure 11 indicate students who were mobile were underrepresented among ALEKS, i-Ready, and ST-Math users, as they accounted for 1%, 2%, and 2%, respectively, of users within their software vendors. Non-mobile students who made up 93% of students in this study, also accounted for the majority of ALEKS (99%), i-Ready (98%), and ST Math (98%) users.

Figure 12. Chronic Absence of Digital Math Software Users in Each Vendor



Data sources: USBE and Digital Math Software Vendors

The student sample in this study was 11% chronically absent and 89% non-chronically absent. Similar to the study sample, digital math software users were mostly comprised of non-chronically absent students. Figure 12 shows that 92% of ALEKS users, 87% of i-Ready users, and 90% of ST Math users were not chronically absent. Chronically absent students, who accounted for a minority of digital math software users across vendors, were slightly more represented among i-Ready users (13%) than ST Math (10%) and ALEKS (8%).

Summary

Similar to the prior section's findings, ALEKS, i-Ready, and ST Math users were composed very similarly to the overall student sample for this study. Like the overall student sample, ALEKS, i-Ready, and ST Math users were mostly White, non-rural, non-chronically absent, non-mobile, and ineligible for free or reduced lunch. While i-Ready and ST Math users were mostly male like the general student sample, ALEKS users were equally distributed by gender. Important deviations from the composition of the overall student sample can be seen in Figure 7, in which Latino students were overrepresented among i-Ready and ST Math users, in Figure 8, in which rural students were overrepresented among i-Ready and ALEKS users, and Figure 10, in which students who were eligible for free or reduced lunch were overrepresented among ST Math users.

Digital Math Software Use Information

How Much and How Consistently Do Students Use Math Software?

This section examines the length of time that students used digital math software per week and the consistency with which students used digital math software. We report the length of time students used digital math software by dividing students into quartiles based on their average minutes of use per week. Students were grouped into quartiles for each year they used a software; this means that if a student used a software for multiple years they are counted multiple times in the use quartiles. Software users were counted in multiple quartiles to allow individuals use to vary over years.

The degree of consistency—how similar students were in the amount of time they used digital math software from month to month with which students used digital math software—was determined using a coefficient of variation (COV). Alternatively, a lower COV indicates lower variation or a greater degree of consistency among students in their use of digital math software.

Findings

Within each vendor, digital math software users were grouped into quartiles based on the average time they spent using digital math software per week. Quartile 1 consists of the 25% of digital math users who spent the least amount of time using the software per week. Quartile 2 consists of the 25% of students who spent the second least amount of time using the software per week. Quartile 3 consists of the 25% of students who spent the second most time using software per week, and Quartile 4 consists of the students who spent the most time using digital math software per week.

Table 3. Range of Minutes of Digital Math Software Use Per Week for Each Quartile of Student Users and for Each Vendor

	ALEKS	*i-Ready*	*ST Math*
	n=157,301	n=27,766	n=39,838
	Minutes of use per week		
Quartile 1	≤41	≤42	≤27
Quartile 2	41 – 60	42 – 55	27 – 40
Quartile 3	61 – 92	56 – 70	41 – 64
Quartile 4	≥93	≥71	≥65

Data sources: USBE and Digital Math Software Vendors

Table 3 provides the breakdown of minutes per week for each use quartile for each of the three vendors included in this evaluation. ST Math had the lowest amount for the first use quartile, which was 27 or fewer minutes per week. ALEKS had the highest amount for use in the fourth quartile, which was 93 minutes or greater per week.

For a comparison, we discuss digital math vendor use recommendations. ALEKS does not currently provide a recommendation for minutes of use per week. ALEKS does post information regarding implementation strategies from their customers which include weekly expected use. Some implementation strategies call for 2 hours of use per week.[7] Other strategies call for 5 hours per week.[8] i-Ready currently recommends students complete 30-49 minutes on software per week.[9] ST Math recommends students complete 90 minutes per week on digital math software.[10]

Table 4. Count of Students in Years for Each Quartile of Digital Math Software Users and for Each Vendor

	ALEKS	*i-Ready*	*ST Math*
	Number of Observations		
Quartile 1	39,326	6,944	9,984
Quartile 2	39,325	6,943	9,990
Quartile 3	39,325	6,942	9,980
Quartile 4	39,325	6,937	9,974
Total	157,301	27,766	39,838

Note that students were included in quartiles for each year they used a digital math software, so students with multiple years of software use are counted multiple times in Table 45.

Data sources: USBE and Digital Math Software Vendors

Data from Table 4 demonstrates that ALEKS had the greatest number of users, followed by ST Math, and i-Ready. Within vendor, each quartile had approximately 25% of users for that vendor.

[7] Implementation Strategies: https://www.ALEKS.com/k12/implementations/popup?_form_=true&parse_list=e*258&parse_request=true&cmscache=parse_list:parse_request#:~:text=Students%20will%20be%20expected%20to,minutes%2C%20four%20days%20per%20week.

[8] Implementation Strategies: https://www.ALEKS.com/k12/implementations/index?_form_=true&parse_request=true&parse_list=h*323&cmscache=parse_list:parse_request

[9] i-Ready Success in Action: https://www.curriculumassociates.com/products/i-ready/how-it-works

[10] T Math Implementation Guide: https://dlassets.stmath.com/pdfs/massachusetts/MA-Implementation-Guide-EN-176.pdf

Table 5. Consistency of Digital Math Software Use by Use Quartile of Student Users for Each Vendor

	ALEKS	*i-Ready*	*ST Math*
	Consistency in use measured by coefficient of variation		
Quartile 1	.62	.60	.64
Quartile 2	.56	.52	.61
Quartile 3	.54	.44	.58
Quartile 4	.53	.41	.60

Data sources: USBE and Digital Math Software Vendors

For each software vendor, we calculated the average of all students COV to assess the degree of consistency with which students in each quartile used digital math software. The methodology section provides a full explanation of how we calculated the COV. The COV is an indicator of the consistency of duration of use from month to month. For example, two students on average may use software 8 hours per month, but one may consistently use it 8 hours each month and the other might use it 4 hours one month and 12 hours another month. Although both students have the same monthly average duration of use, the consistency with which they use the software is different. As previously explained, a higher COV indicates higher variation or a lower degree of consistency of use of digital math software. Alternatively, a lower COV indicates lower variation or a greater consistency of use of digital math software.

As Table 5 shows, across all three software vendors, students in Quartile 1, the quartile with lowest use per week, had the lowest degree of consistency in their use of digital math software (i.e., these students had the highest coefficient of variation). Among ALEKS and i-Ready users, consistency in use of digital math software increases with each quartile; students in Quartile 4 exhibited the highest degree of consistency in their software use. For ST Math users, students in Quartile 3 demonstrated the greatest consistency in using the software. Students in i-Ready in the 4th use quartile had the lowest COV or were the most consist users across all four software vendors.

Summary

In summary, the length and consistency of digital math software use varies across students and vendors. With the exception of ST Math users, students who used the software the most, that is, students in Quartile 4, also had the lowest average COV, showing that they use digital math software more consistently from month to month compared to users in lower percentiles.

Digital Math Software Users and Non-Users Math Performance

Do Software Users Perform Better than Non-Users?

To assess differences between users and non-users on SAGE math tests, we examined averages and general estimating equation regression results for proficiency, student growth percentile (SGP), and percentile rank. First, we report averages on these outcomes for users and propensity-score matched non-users. Then we present results of regression analyses that calculate the difference in outcomes for digital math software users compared to non-users.

Table 6 shows that digital math software users and propensity-score matched non-users had similar average proficiency levels, SGP, and percentile rank. The averages of digital math software users were slightly above non-users. In previous reports, Digital math software users had higher average SGP than non-users

3 Outcomes of Interest

1. Proficiency. Measures student performance relative to a predefined benchmark.
2. Percentile Rank. An indicator of students performed relative to other students who took the same test.
3. Student Growth Percentile (SGP). A statistical estimate of student growth relative to students who had similar performance in the past.

See Appendix A. Methodology for additional Information about outcome measures.

Findings

Table 6. Average Proficiency Level, Student Growth Percentile, and Percentile Rank for Users and Propensity-Score Matched Non-Users

	Proficiency (1-4)		Percentile Rank		Student Growth Percentile (SGP)	
	Average	SD	Average	SD	Average	SD
Users	2.33	1.12	49.96	24.20	50.91	28.73
Propensity Score Matched Non-users	2.32	1.13	48.48	23.71	49.72	28.98

Data sources: USBE and Digital Math Software Vendors

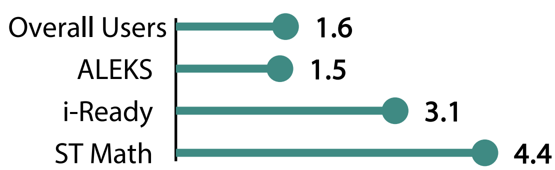
Regression analyses provide more robust tests of the relationship between software use and performance, because they control for other characteristics that may be related to performance. In the regression analysis, we controlled for several student characteristics, including gender, race or ethnicity, free and reduced lunch status, mobility, and chronic absenteeism. In addition to student characteristics, we controlled for school-level variables, including rates of low income, mobility, and chronic absence. Results of student and school-level variables included in regression models are presented in the next section. The focus of this section is regression results estimating the difference between digital math software users and propensity-score matched non-users on the outcomes of interest: proficiency, percentile rank, and SGP.

Figure 13. Difference in Probability of Proficiency for Digital Math Software Users Compared to Propensity-Score Matched Non-Users

Data sources: USBE and Digital Math Software Vendors

Figure 13 shows the regression models' estimated difference in the probability of students meeting proficiency for users and propensity-score matched non-users. The model estimated that digital math software users across the three years of use had a 1.7% higher probability of being proficient compared to propensity-score matched non-users. When we consider results by software vendor, ALEKS users were not statistically significantly more or less likely to be proficient compared to matched non-users, but i-Ready users had 4.9% higher probability of proficiency, and students using ST Math had 9.7% higher probability of proficiency compared to non-users. Next we present regression results for the outcome of percentile rank.

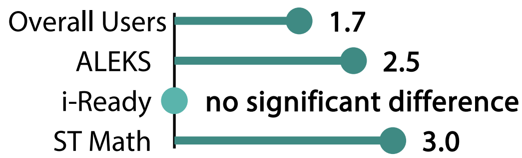
Figure 14. Difference in Percentile Rank of Proficiency for Digital Math Software Users Compared to Propensity-Score Matched Non-Users



Data sources: USBE and Digital Math Software Vendors

As shown in Figure 14, regression models estimated the difference in percentile rank between digital math software users and propensity-score matched non-users. The model for all digital math software users estimated that software users on average had 1.6 higher percentile ranks than propensity-score matched non-users. To illustrate this finding, if a student who did not use digital math software scored better than 68% of her peers, we would expect a similar student who did use digital math software to score better than 69.6% of her peers. When considering individual software vendors, regression models estimated ALEKS users had 1.5 higher percentile ranks than matched non-users, i-Ready users had percentile ranks 3.1 higher than matched non-users, and ST math users had percentile ranks 4.4 higher than matched non-users. Next we present regression estimates of SGP for digital math software users and non-users.

Figure 15. Difference in SGP for Digital Math Software Users Compared to Propensity-Score Matched Non-Users



Data sources: USBE and Digital Math Software Vendors

Figure 15 shows the regression models estimates of the difference in SGP for digital math software users and propensity-score matched non-users. The model for all digital math software users estimated that on average, users' SGPs were 1.7 points higher than non-users. Considering users of the vendors separately, regression models estimated ALEKS users' average SGP was 2.5 points higher than non-users, but regression results showed i-Ready users did not have statistically significantly different SGP compared to propensity-score matched non-users. The regression model estimated that ST Math users on average had 3 point higher SGP than matched non-users. In the next section, we present regression results showing how student and school level variables are related to the three outcomes of interest. See Appendix B: GEE Regression Results for Digital Software Users and Non-Users for full results of the regression models for the three outcome indicators for each vendor.

Summary

Findings presented in this section address the question of whether digital math software users performed better than propensity-score matched non-users on SAGE tests across multiple years. Performance indicators include proficiency, percentile rank, and SGP. This analysis suggest digital math software users performed slightly better than propensity-score matched non-users.

- Digital math software users average proficiency level, percentile rank and SGP were only slightly above averages of propensity-score matched non-users.
- Regression models estimated overall digital math software users and i-Ready and ST Math users were a little more likely to be proficient compared to propensity-score matched non-users.
- Regression models estimated overall digital math software users and users of all three vendors had higher percentile ranks than propensity-score matched non-users.
- Regression models estimated overall digital math software users and ALEKS and ST Math users had higher SGP than propensity-score matched non-users.
- The size of effects varied across vendors.

Student and School Characteristics and Performance

What Student and School Characteristics are Related to Performance?

In the previous section, we presented results that showed software users performed better than non-users in terms of proficiency, percentile, and SGP. In our GEE analyses we controlled for several student and school-level characteristics. In this section, we report the relationship between those control variables and performance.

Findings

Table 7 provides estimated difference (Δ) in the three outcome indicators based on the student and school characteristics. Table 7 also indicates the direction of the relationship. A positive relationship, indicated by an arrow pointing up, means that students with the characteristic performed better than students without the characteristic. A negative relationship, which is indicated by an arrow pointing down, means that the students with the characteristic performed worse than students without the characteristic. Arrows pointing left and right indicate that students with the characteristic performed better on one or more indicator, but worse on another one or more indicator than students without the characteristic. We reported n.s. in place of model estimates which were not statistically significant.

Table 7. GEE Results for Student and School Characteristics

Characteristic	Δ in Probability of Proficiency	Δ in Percentile	Δ in SGP	Direction of Relationship
Gender				
Male	1.3%	-0.9	-1.7	Mixed ←→
Race or Ethnicity				
Asian	3.1%	2.4	4.5	Pos ↑
Multiple Races	-3.9%	-3.4	n.s.	Neg ↓
Pacific Islander	-16.9%	-12.4	n.s.	Neg ↓
Hispanic/Latino	-20.8%	-17.2	-2.2	Neg ↓
American Indian	-23.8%	-18.4	n.s.	Neg ↓
African American	-26.5%	-25.3	-3.7	Neg ↓
Additional Student Characteristics				
Rural	1.1%	1.1	1.0	Pos ↑
Mobile	-10.9%	-9.6	-3.6	Neg ↓
Free and Reduced Lunch	-14.0%	-12.5	-1.9	Neg ↓
Chronic Absent	-15.3%	-13.5	-5.6	Neg ↓
School-Level Variables				
Mobile	-0.6%	-0.5	-0.2	Neg ↓
Free and Reduced Lunch	-0.1%	-0.1	0.0	Neg ↓
Chronic Absence	0.3%	0.1	0.2	Pos ↑

Data sources: USBE and Digital Math Software Vendors

Gender, race or ethnicity, additional student characteristics, and school characteristics were statistically significantly related to outcomes. Gender was the only student characteristic that was associated with both improved and worse performance, depending on the indicator. Male students were just over 1% more likely to be proficient compared to female students, but on average had lower scale scores and lower SGP. The most likely explanation for these findings is that whereas a slightly higher percent of male students met proficiency, there were a number of male students with very low scores, which decreased the average percentile rank and SGP for male students.

Compared to White students, Asian students performed better on all three indicators, probability of proficiency, percentile rank, and SGP. Students with multiple race or ethnicity, Hispanic or Latino students, American Indian students, and African American students on average did not perform as well as White students across the indicators. Pacific Islanders did not perform as well as White students on the proficiency outcome and the percentile outcome, but were not statistically significantly different compared to White students on SGP. The effects for Hispanic/Latino, American Indian, African American and Pacific Islander were of greater magnitude than other student or school characteristics.

On all three indicators, probability of proficiency, percentile rank, and SGP, rural students tended to perform a little better compared to non-rural students. Students characteristics of being mobile, qualifying for free and reduced lunch and being chronically absent were related to lower scores on the three indicators. Similarly, students who attended schools with high rates of mobile and low-income, students did not perform as well as students in other schools. Surprisingly, students in schools with high levels of chronic absence performed slightly better. See the full model for all users in Appendix B: GEE Regression Results for Digital Software Users and Non-Users. See the full models for each vendor in Appendix C. Vendor Specific Regression Results for Digital Math Software Users and Non-Users.

Summary

Findings presented in this section address the question of what student and school-level characteristics were related to performance indicators. Multiple student and school characteristics were significantly related to performance indicators. Student characteristics related to outcome indicators included gender, race and ethnicity, rural status, mobility, whether students qualify for free and reduced lunch, and chronic absence. At the school level, overall rates of mobility, students who qualify for free and reduced lunch, and chronic absence were related to outcome indicators.

- Gender had the only mixed relationship, with male students being more likely to be proficient, but also having overall lower average percentile rank and SGP.
- Asian students on average performed better than White students across all indicators.
- Students of multiple race or ethnicity, Pacific Islander, Hispanic or Latino, American Indian, and African American students did not perform as well as White students across the three indicators.
- Rural students performed slightly better than non-rural students across all three indicators.

- On all three indicators, mobile students, students who qualify for free and reduced lunch, and chronically absent students did not perform as well as students who respectively were not mobile, did not qualify for free and reduced lunch, and were not chronically absent.
- Students in schools with higher rates of mobility and students who qualify for free and reduced lunch did not perform as well as students in schools with lower rates of mobile students and students who qualify for free and reduced lunch.
- Students in schools with higher rates of chronic absence performed better than students in schools with lower rates of chronic absence.

Amount and Consistency of Digital Math Software Use and Performance

How Does the Way Students Use Math Software Relate to Performance?

In this section of the report, we examine how student use of digital math software related to performance across the indicators of probability of proficiency, percentile rank, and SGP. In this section we report on all digital math software users. See regression results for the individual vendors in Appendix E. Vendor Specific Regression Results for Digital Math Software Users Only. The variables of interest for software use include:

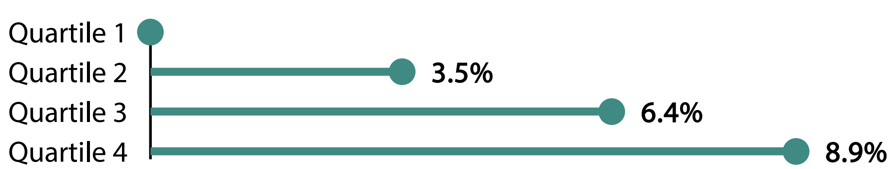
1. Overall use as measured by use quartiles
2. Consistency of use as measured by the coefficient of variance
3. Years of software use within vendor

Because this section is concerned with how students used digital math software, the regression analyses we report on in this section included digital math software users and did not include the propensity-score matched comparison group. The regression models reported on here controlled for student and school-level characteristics reported on in the last section, but we only report on use variables in this section. See results of the full model for all users in Appendix D. Regression Results for Digital Software Users Only.

Findings

First, we present findings on how overall minutes of use per month was related to performance. We used the use quartiles reported on previously in this report as predictors in models. Quartile 1 consists of the 25% of students with the lowest use. Quartile 2 two consists of the 25% of students with the next lowest use. Quartile 3 consists of the 25% of students with the second highest use, and Quartile 4 consists of the 25% of students with the highest use. Note that the range of minute per month included in each quartile varied from vendor to vendor.

Figure 16. Difference in Probability of Proficiency for Use Quartiles



Data sources: USBE and Digital Math Software Vendors

We used Quartile 1 as our baseline for comparison so we could compare the difference in outcome indicators between Quartile 1 and Quartiles 2-4. Results shown in Figure 16 indicate that students who use digital math software more were more likely to be proficient. Users in

Quartiles 2-4 had respectively 3.5%, 6.4%, and 8.9% higher probabilities of proficiency compared to users in the Quartile 1.

Figure 17 shows that similar to proficiency, students who used digital math software more had higher percentile ranks. Compared to Quartile 1, students in Quartiles 2-4 had respectively 3.27, 6.48, and 8.97 higher average percentile ranks. To illustrate this finding, if a student in Quartile 1 has a percentile rank of 60, he scored higher than 60% of other test takers. A similar student in Quartile 4 would have a percentile rank of 69, indicating he scored higher than 69% of other test takers.

Figure 17. Difference in Percentile Rank for Use Quartiles

Data sources: USBE and Digital Math Software Vendors

As shown in Figure 18, similar to findings for proficiency and percentile rank, students who used digital math software more had higher SGP. Compared to digital math software users in Quartile 1, users in Quartiles 2, 3, and 4 respectively, had 2.88, 5.11, and 7.45 higher SGP. To illustrate, if a Quartile 1 student had SGP of 53, she would have more growth or greater improvement than 53% of test takers who scored similar to her the previous year. We would expect a similar Quartile 4 student to have an SGP of 60, indicating that she would have more growth or greater improvement than 60% of test takers who scored similar to her the previous year.

Figure 18. Difference in SGP for Use Quartiles

Data sources: USBE and Digital Math Software Vendors

In addition to overall use, we included consistency of use and years of use in the model to test their relationship to performance. The coefficient of variation is an indicator of how consistent or inconsistent a student used digital math software. We calculated the coefficient of variation for each student across all years of use. Table 8 shows results for consistency of use and years of use.

Table 8. Difference in Outcomes of Interest Given a One-Unit Increase in the Coefficient of Variation and an Additional Year of Use

Use Variable	Difference in Probability of Proficiency	Difference in Percentile	Difference in SGP
Coefficient of Variation	-2%	-2.1	-1.9
Years of Use	-3%	-.1	-1.2

Data sources: USBE and Digital Math Software Vendors

Students who were more consistent in their use of digital math software performed better on all three outcome indicators. The coefficient of variation is a measure of how inconsistently students use software; the higher the coefficient of variation, the more variation in the length of time students used the software for each month. The regression estimates that a student with a 1% higher coefficient of variation was 2% less likely to be proficient, had a 2.1 lower percentile rank, and a 1.9% lower SGP.

Results indicate that students who used digital math software more years did not perform as well as students who used the software fewer years. For each additional year of digital math software use, students were 3% less likely to be proficient, had a .1 lower percentile rank, and a 1.2 lower SGP. See Appendix D. Regression Results for Digital Software Users Only, and Appendix E. Vendor Specific Regression Results For Digital Math Software Users Only.

Summary

In this section, we looked at how the way students used digital math software related to the outcome indicators of probability of proficiency, percentile rank, and SGP. Findings suggest that overall amount of use and consistency of use of digital math software were related to the three indicators of performance. Years of digital math software use was negatively related to SAGE math performance.

- Students in higher use quartiles had higher probability of proficiency, percentile ranks, and SGP, meaning that more use was related to better performance.
- Students with higher coefficients of variation had lower probability of proficiency, percentile ranks, and SGP, indicating students who used digital math software more consistently performed better than students who had less consistent use.
- More years of digital math software use was associated with lower probability of proficiency, percentile scores, and SGP, indicating that students who used digital math software multiple years did not perform as well as students who only used it one year.

Summary of Findings

Here we provide a summary of the overall evaluation findings. In this evaluation we compared digital math users to non-users across the state. We also analyzed use, including how much and how consistently students used the digital math software. We compared users and non-users on SAGE math test outcome indicators of probability of proficiency, percentile rank, and SGP. We also explored which student and school-level characteristics are related to performance indicators and finally how use of digital math software is related to SAGE performance indicators. Findings in all of these areas are summarized below.

Digital Math Software User and Non-User Information

Digital math software users and non-users statewide had similar rates of students in each race and ethnicity, gender, and similar rates of mobile students and students who were chronically absent. Digital math software users had slightly higher rates of students in rural areas and slightly higher rates of students who qualify for free and reduced lunch.

Comparing users across Digital Math Software Vendors, students using each vendor's software appear similar in terms of most student characteristics. However, compared to ALEKS, i-Ready and ST Math digital software users had higher rates of Latino students. Compared to ST Math, i-Ready and ALEKS users had higher rates of rural students. ST Math software users had a higher percent of students eligible for free and reduced lunch.

Digital Math Use and Consistency of Use

The amount of time students spent using digital math software varied between students within and across software vendors. Similarly, how consistently students used digital math software varied between students within and across software vendors. In general, consistency of use increased as time spent using digital math software increased.

Digital Math Software Users and Non-Users Math Performance

Average proficiency level, percentile rank, and SGP were similar in digital math software users and non-users. With the exceptions noted below, regression results suggested digital math software users performed slightly better than non-users in probability of proficiency, percentile rank, and SGP. Exceptions include ALEKS users were not statistically significantly more likely to be proficient than propensity-score matched non-users, and i-Ready users did not have significantly higher SGP than propensity score matched non-users.

Student and School Characteristics and Performance

Compared to female students, male students were slightly more likely to be proficient, but had lower average percentile ranks and SGP. Race and ethnicity were related to performance. In general, Asian students performed better than White students, and other students of color did not perform as well as White students. Rural students performed slightly better than non-rural students across the three outcome indicators. Mobile students, students who qualify for free and reduced lunch, and students who were chronically absent did not perform as well as students without those attributes. Lastly, students from schools with higher levels of mobile students and students who qualify for free and reduced lunch did not perform as well as students from schools with lower rates of mobility and students who qualify for free and reduced lunch, and students from schools with higher rates of chronic absence performed better than students from schools with lower rates of chronic absence.

Amount and Consistency of Digital Math Software Use and Performance

Students who used digital math software more minutes per week, based on use quartile, were more likely to be proficient, had higher percentile ranks and higher SGP. Students who used digital math software more consistently (had less variation in the length of use from month to month) were more likely to be proficient, had higher percentile ranks and higher SGP. Finally, students who used digital math software for multiple years were less likely to be proficient, and had lower percentile ranks and SGP.

Causality and Quality of Use

Two issues of interest that are not settled by this evaluation are whether use of math software causes improved performance and with what quality teachers use digital math software and integrate software into curriculum. Consistent with previous evaluations and research on technology in mathematics education (Murphy, 2016; Cheung & Slavin, 2013; Young, Gorumek, & Hamilton, 2018), this evaluation found that software users performed better than non-users. The outcome of interest for this evaluation was multiple years of SAGE math test proficiency, percentile rank, and SGP. The analyses reported here, and previous years of the evaluation, have been observational and correlational in nature. These types of studies are important. Yet, they do not demonstrate causation. In the absence of experimental designs—randomly assigning students and schools to use or not use digital math software, an evaluation cannot definitively speak to whether the software caused the improved performance in users, and such conclusions should be avoided. However, the additional analyses using propensity score matching strengthens the causal argument, as we have controlled for preexisting differences between users and non-users. However, it is important to note that propensity score matching only accounts for characteristics we included in the propensity score matching. Additional student and school characteristics may influence performance, and certainly school policies and teacher practices, which were not addressed at all in these analyses impact performance.

This analyses also does not address the quality of use and how teachers integrate digital math software and curriculum. However, in subsequent evaluations, informed by the SAMR model (Puentedura, 2013) and the TPACK framework (Mishra & Koehler, 2006), we explore student and teacher perceptions of how digital math software is being used in classrooms. The UEPC has collected survey data from students and teachers as well as teacher interviews to better understand how personalized math software is used in teaching and learning. However, to date, the use of these surveys are not permitted to be administered in a way that would permit the data between sources—surveys, teacher- and student-level data, and observations—to be used in tandem.

Considerations for Improving the K-12 Math Personalized Learning Software Grant

We conclude this report with some considerations for K-12 Math Personalized Learning Software Grant. These considerations are based on evaluation findings and research on technology and education. The considerations we present address efforts to improve outcomes by increasing use and consistency of use of digital math software, expanding high quality integration of digital math software into teaching and learning, and providing additional supports for students.

The K-12 Math Personalized Learning Software Grant seeks to improve student learning in mathematics literacy. We found students who use digital math software more and students who use digital math software with greater consistency outperform students who use the software less and use software with less consistency. Research suggests that distributing practice consistently across time can be more effective than mass practice at one time (Nazari & Ebersback, 2019; Schutte et al., 2015).

Next, this evaluation demonstrates better outcomes for students who used the software more and students who used software more consistently. However, there is more to achieving successful outcomes than amount and consistency of use. Research on educational technology underscores the importance of effective integration of technology into curriculum (Puentedura, 2013; Mishra and Koehler, 2006), including the quality of technology integration.

To address both the quality and quantity of digital software integration, there are several recommendations. First, consider creating a digital math integration repository that illustrates how teachers are both integrating the software in their mathematics lessons and how they are finding the balance between consistent and meaningful use of the digital math software. Next, increase opportunities for learning for educators to model and practice technology integration within the mathematics program that addresses increased and consistent use of the digital math software as a complement to, and not a replacement for, their mathematics instruction. This professional learning could include addressing how teachers may leverage available software reports of student use and performance to address student needs. Taken together, these opportunities would provide a venue for teachers to share their professional practice, success stories and strategies to overcome barriers or obstacles to successful integration of digital math software into math curriculum.

Many students of color, students who qualify for free and reduced lunch, mobile students, and students who were chronically absent were less likely to be proficient and had lower percentile ranks and SGP. Issues relating to multicultural education and inequities in education cannot be solved by technology alone and must be addressed systemically. However, addressing inequities in technology access and use is necessary to address these larger issues, including pedagogy, educator and student beliefs, and access (Gorski, 2009; Dotterer, Hedges, & Parker, 2016). One aim of the digital math software is to increase opportunities in mathematics. In order to increase access and improve student outcomes in mathematics literacy for student groups with lower performance, there are several considerations that may be beneficial. First, explore how access and use of the software may differ for student groups based on observed classroom-level practices. Next, provide intentional development opportunities for educators to maximize culturally relevant pedagogy for students and increase access to the software in ways that again complement other instructional techniques. Finally, further consideration may be needed regarding the availability and access to the digital math software.

References

Bebell, D. (2005). *Technology Promoting Student Excellence: An Investigation of the First Year of 1:1 Computing in New Hampshire Middle Schools.* Technology and Assessment Study Collaborative, Boston College, Chestnut Hill, MA.

Blazer, C. (2008). *Literature review: Educational Technology.* Research services, Miami-Dade County Public Schools. Miami-Dade: Research Services Office of Assessment, Research, and Data Analysis Miami-Dade County Public Schools. https://files.eric.ed.gov/fulltext/ED536868.pdf

Bonifaz, A., & Zucker, A. (2004). *Lessons Learned About Providing Laptops for All Students.* Northeast and the Islands Regional Technology in Education Consortium. Retrieved from http://www.oberlin.k12.oh.us/onetoonedocs/LaptopLessonsRprt.pdf.

Bray, A., & Tangney, B. (2017). Technology usage in mathematics education research – A systematic review of recent trends. Computers & Education, 114, 255–273. doi:10.1016/j.compedu.2017.07.004

Cambridge Assessment International Education. (2018). *Global Education Consensus*. Cambridge International. https://www.cambridgeinternational.org/Images/514611-global-education-census-survey-report.pdf

Cheung, A.C.K. & Slavin, R.E. (2013). The effectiveness of educational technology applications for enhancing mathematics achievement in K-12 classrooms: A meta-analysis. *Educational Research Review, 9,* 88-113, 10.1016/j.edurev.2013.01.001

Dotterer, G., Hedges, A., & Parker, H. (2016). The digital divide in the age of the connected classroom: How technology helps bridge the achievement gap [White paper]. NetRef. https://net-ref.com/wp-content/uploads/2016/01/Bridging-the-Digital-Divide-NetRef-White-Paper-FINAL.pdf

Dunleavy, M., Dexter, S., & Heinecke, W.F. (2007). What Added Values Does a 1:1 Student to Laptop Ratio Bring to Technology-Supported Teaching and Learning? *Journal of Computer Assisted Learning, 1*(1). Retrieved from http://pkp.sfu.ca/ojs/demo/present/index.php/jce/article/view/171/56

Franklin, J.D., Orians, E., Nicholson, A. & Rorrer, A.K. (2016). *Technology in the Classroom: Strategies, Potential Benefits, & Challenges of Device Adoption*. Utah Education Policy Center. Salt Lake City, UT. https://daqy2hvnfszx3.cloudfront.net/wp-content/uploads/sites/2/2019/02/26091452/Technology-in-the-Classroom.pdf

Gorski, P. C. (2009). Insisting on digital equity: Reframing the dominant discourse on multicultural education and technology. Urban Education, 44(3), 348–364. https://journals.sagepub.com/doi/pdf/10.1177/0042085908318712?casa_token=PrzV-QDIzFAAAAAA:_bVvtOEe44wewuYl1uRcV056dG0WKAIwByeORZ3qOMyho8f3-b2fIdsAv1SdFFy49zGb8Tt9gzJpZw

Hardman, J. (2019). Towards a pedagogical model of teaching with ICTs for mathematics attainment in primary school: A review of studies 2008-2018. *Heliyon 5*(5), https://doi.org/10.1016/j.heliyon.2019.e01726

IFC Consulting Services Ltd. (2015). *Literature Review on the Impact of Digital Technology on Learning and Teaching*. The Scottish Government. (ISBN: 9781785448195). https://dera.ioe.ac.uk/24843/1/00489224.pdf

Jobe, H., & Peck, K.L. (2008). *Classrooms for the Future (CFF): Preliminary Results.* Presentation at the Pennsylvania Educational Technology Expo and Conference, Hershey, PA, February, 2008.

Koh, J.H.L., Chai, C.S., & Lim, W.Y. (2017). Teacher professional development for TPACK-21CL: Effects on teacher ICT integration and student outcomes. *Journal of Educational Computing Research 55*(2), 172-196. https://journals-sagepub-com.ezproxy.lib.utah.edu/doi/full/10.1177/0735633116656848

Mishra, P. & Koehler, M.J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record 108*(6), 1017-1054. http://one2oneheights.pbworks.com/f/MISHRA_PUNYA.pdf

Murphy, D. (2016). A literature review: The effect of implementing technology in a high school mathematics classroom. *International Journal of Research in Education and Science (IJRES), 2*(2), 295-299. https://files.eric.ed.gov/fulltext/EJ1105104.pdf

Nazari, K.B., & Ebersback, M. (2019). Distributed practice in mathematics: Recommendable especially for students on a medium performance level? *Trends in Neuroscience and Education 17*, 1-10. https://www.sciencedirect.com/science/article/pii/S2211949319300183?via%3Dihub

Puentedura, R. R. (2013). SAMR: Moving from enhancement to transformation. Retrieved from http://www.hippasus.com/rrpweblog/archives/2013/05/29/SAMREnhancementToTransformation.pdf

Shulman, L. (1986). Those who understand: Knowledge growth in teaching. Educational Researcher, 15(2), 4-14. https://www.wcu.edu/WebFiles/PDFs/Shulman.pdf

Schutte, G.M., Duhon, G.J., Solomon, B.G., Poncy, B.C. Moore, K., Story, B. (2015). A comparative analysis of massed vs. distributed practice on basic math fact fluency growth rates. *Journal of School Psychology 53*, 149-159. https://www.sciencedirect.com/science/article/pii/S0022440514001034?via%3Dihub.

Waddoups, G.L. (2004). Technology Integration, Curriculum, and Student Achievement: A Review of Scientifically Based Research and Implications for EasyTech. Portland, OR: Learning.com. Retrieved from http://www.learning.com/documents/Learning.com_WP_Summary.pdf

Young, J., Gorumek, F. & Hamilton, C. (2018). Technology effectiveness in the mathematics classroom: A systematic review of meta-analytic research. *The Journal of Computer Education, 5*(2), 133-148. https://www.researchgate.net/publication/325105360_

[Technology effectiveness in the mathematics classroom a systematic review of meta-analytic research](Technology_effectiveness_in_the_mathematics_classroom_a_systematic_review_of_meta-analytic_research)

Cover image: Monkey Business Images/Shutterstock.com

Appendix A. Methodology

Data Collection Channel

The UEPC set up a dedicated secure file transfer protocol server for software vendors. All data exchanges between the UEPC and the vendors, schools, school districts, and USBE were compliant with FERPA and other federal and local privacy and confidentiality laws and regulations.

Data Disposition

This is a longitudinal study. All data that the UEPC received and derived from the received data will be used solely for this project and will be kept until the project ends. The UEPC will not share the linked data to any third party under any circumstances. The UEPC will not share any data components to any third party without formal written authorization by those who own the data components along with documentation of IRB approval from the third party's institution.

Once the project ends, all data will be sanitized and destroyed following the guideline of the University of Utah (http://regulations.utah.edu/it/guidelines/G4-004N1.pdf) and the Federal regulations (http://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.800-88r1.pdf, pp 22-23).

Data Source Security

All data were securely encrypted, transmitted, and stored according to industry and University of Utah standards.

Data Sources

Vendor Data

Three math learning platforms were included in the evaluation, including ALEKS, i-Ready, and ST Math. Mathspace was not included in this analysis because for the years required to do a longitudinal view they were still a pilot program, and therefore didn't have the data necessary for this analysis. Imagine Math was not included in this analysis because of issues in data that made matching across platforms (i.e. vendor provided data to SAGE data) inaccessible. Usual yearly evaluation reports can still be expected per usual arrangement. Student usage from vendors was requested every month for longitudinal analyses starting in September 2014 and going through November 2019.

USBE Data

In accordance with the existing data-sharing agreement, the USBE data needed for the evaluation of the software were transferred to the UEPC via the USBE's secure FTP server.

Data Storage

The Utah Education Policy Center (UEPC) considers the security and protection of data to be of the utmost importance. Encrypted data are stored on secure hardware, maintained by highly trained computer professionals, and safeguarded by the University of Utah's network security, Virtual Private Network (VPN), and firewall. The UEPC protects data in compliance with the

Family Educational Rights and privacy Act, 20 U.S. Code §1232g and 34 CFR Part 99 ("FERPA"), the Government Records and Management Act U.C.A. §62G-2 ("GRAMA"), U.C.A. §53A-1-1401 et seq, 15 U.S. Code §§ 6501-6506 ("COPPA") and Utah Administrative Code R277-487 ("Student Data Protection Act").

The UEPC limits and restricts data access to leaders in charge of the day-to-day operations of the research, and professional and technically qualified staff who conduct research. All UEPC staff receive FERPA and CITI trainings and certification, which cover issues of data privacy, security, and protections, and ethics of data management and use. UEPC employees who have access to data are required to sign a Non-Disclosure Agreement. Access to data is controlled by password protection, encryption, dual authentication, and/or similar procedures designed to ensure that data cannot be accessed by unauthorized individuals.

The UEPC maintains a data sharing agreement (DSA) with the Utah State Board of Education (USBE) wherein the USBE shares data with the UEPC for the purposes of state, district, and federal evaluations.

Data Samples

The sample used for the analyses included all students whose data from the five vendors matched with the USBE database. Students were in grades 3 through 12 because those grades completed SAGE testing. Samples in the analyses varied depending on the outcomes of interest. Those outcomes included SAGE standardized scores, standardized growth percentiles (SGPs), and proficiency level. The largest sample was for proficiency, because it included the least amount of missing values compared to the other outcomes. The analysis of SAGE raw scores included a subset of the full population because it only included students who had SAGE math test scores. The SGP analysis was smaller still because it only included students in grade four or above who took the SAGE math test in at least one previous year.

Some students used more than one software program. Because these students represented less than 1% of the total students who used the software, we did not think they would affect the outcome of the analyses. For the analyses of the combined vendors, students were counted only once per year and their number of minutes on the software was combined across the software programs they used.

Sample sizes reported in this analysis are complex due to the nature of analysis related to repeated measures. Sample sizes throughout various analyses were different due to a number of factors such as missing data among different variables, reporting of observations vs reporting distinct individuals, and construction of different variables.

Data Analyses

Data Matching Methods

We linked the vendor data with USBE data using multiple criteria. First, we collapsed the students in the Vendor data to single rows based on the student login and school year, and removed the 2019 and 2020 school years because they contained testing from RISE instead of the SAGE for the outcome. Second, we matched the USBE and Vendors data based on the same full name, state school id, and school year which was appropriate because it yielded a large enough sample for analysis. Third, we identified what schools were associated with each vendor and which schools were not associated with a vendor, and for each individual vendor we performed a propensity score match based on proportions of school-level characteristics with those identified as not having a vendor.

Statistical Analyses

The following statistical methods were used in the analysis:

1. Proportions were reported to compare race, gender, low income status, mobility, rural status, and chronic absenteeism for users and non-users, and between vendors by school year.
2. Consistent with our previous evaluation reports, we considered usage greater than 3600 minutes in a single month, or approximately 14 hours a week, to be unrealistic. Therefore, if a student had a monthly usage greater than 3600 minutes were dropped; this constituted less than 1% of all individuals. Students in the vendor data who had zero minutes of reported usage and zero logins were considered non-users, and were also filtered out of the analysis.
3. Quartiles, which by definition are when you divide the data of interest into 4 equal sized groups, were created by software usage in minutes per week for each vendor independently. This helps to compare low to high usage groups in an interpretable way in the modeling.
4. Proportions for race, mobility status, rural status, those who tested below grade level, chronic absenteeism, and gender were made on the school level in order to perform propensity score match between schools of each vendor individually and non-user schools. This was done to get a more appropriate comparison group for the analysis of users to non-users.
5. All the models used in this analysis accounted for the following variables to help address potential confounding and answer research questions of interest: Years in vendor, Student gender, race, low income status, mobility status, rural status, and chronically absent status; some school level variables were also incorporated in the models such as proportion of low income, mobile, and chronically absent students. It should also be noted that since SAGE testing does not have raw scores that are comparable from one test to another we created standardized test scores to use in our analysis.
6. Generalized Estimating Equation (GEE) with logistic regression was used to compare individual vendor users and combined vendor users to non-users on proficiency with an exchangeable correlation structure. GEE was necessary in this analysis to control for within subject variation because we have repeated measures across years of the same subjects which influences the independence assumption. GEE is similar to its commonly used counterpart generalized linear model in interpretation. In order to have a more balanced model we took a random sample of the USBE non-users that was twice as large as the user group, so the ratio for controls to users would be 2:1.
7. GEE with linear regression was used to compare SGPs and Standardized test scores of individual vendor users and combined vendor users to non-users using an exchangeable correlation structure. In order to have a more balanced model we took a random

sample of the USBE non-users that was twice as large as the user group, so the ratio for controls to users would be 2:1.

8. In order to account for the effect consistency of software use from one month to another on outcomes we generated a coefficient of variation, using the following formula: $C_v = \frac{\sigma_{Period\ Usage}}{\mu_{Period\ Usage}}$, to include in our other within vendor models.
9. GEE with logistic regression was used to determine how the number of minutes per week, divided into quartiles, using the math software influences their proficiency. An exchangeable correlation structure was used to address the within subject variation, and odds ratios comparing the lowest quartile of use to the other three quartiles, 95% confidence intervals of odds ratios, and p-values were reported.
10. GEE with linear regression was used to determine how the number of minutes per week, divided into quartiles, using the math software influences Standardized test scores and SGP. An exchangeable correlation structure was used to address the within subject variation, and coefficients of program use, 95% confidence intervals, and p-values were reported.

Limitations

1. Name spelling variations and typos in the data may impact matching.

2. The SAGE testing takes place starting in 3rd grade, but some of the math vendors begin as early as kindergarten. This means that students who started earlier do not have the year over year data included to account for their full participation in the software.

3. Data on student usage were reported for the entire school year from September to June, including usage that may have taken place after SAGE testing. Program use that took place after a student took the math SAGE test would have no relationship to SAGE results. Therefore, there was some amount of use data included in the analyses that were not relevant to the outcome variables.

4. Student usage amounts may be slightly biased if students remained signed into the program while it was not in use. This influences the maximum values of the software usage quantiles to appear unrealistic in relation to ALEKS and ST Math. These extreme values made up 0.4 % and 0.8 % of the vendor specific samples respectively. Analysis was done to assess the influence of these extreme values, and they were found to be not significantly, or meaningfully, impactful thus by virtue of commonly accepted statistical practice they were left in the analysis. The recommendation to control this issue in the future is extended to the vendors to remain vigilant in controlling for unrealistic time amounts through methods such as monitoring inactivity, setting a plausibility threshold for usage amounts, and/or ex post facto data cleaning.

Appendix B: Regression Results for Digital Software Users and Non-Users

Table 9. Probability of Proficiency Regression Results for Digital Math Users (All Vendors) and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.461	0.008	3395.862	<.001	1.586	.613
Years of use	-0.121	0.006	366.499	<.001	0.886	.470
Software user	0.067	0.010	40.970	<.001	1.069	.517
Gender – Male	0.052	0.006	77.571	<.001	1.054	.513
Black/African American	-1.182	0.031	1500.625	<.001	0.307	.235
American Indian	-1.034	0.033	983.091	<.001	0.356	.262
Asian	0.125	0.022	31.051	<.001	1.133	.531
Hispanic/Latino	-0.884	0.009	8694.064	<.001	0.413	.292
Multiple Races	-0.156	0.019	66.056	<.001	0.855	.461
Pacific Islander	-0.706	0.026	717.790	<.001	0.494	.331
Low Income	-0.577	0.007	6826.196	<.001	0.561	.360
Mobile	-0.442	0.014	1021.859	<.001	0.642	.391
Rural	0.045	0.010	20.599	<.001	1.046	.511
Chronically Absent	-0.633	0.011	3402.546	<.001	0.531	.347
Free and Reduced Lunch	-0.005	0.000	857.095	<.001	0.995	.499
Mobile (school)	-0.025	0.001	701.891	<.001	0.975	.494
Chronically Absent (school)	0.011	0.001	266.161	<.001	1.011	.503

Data sources: USBE and Digital Math Software Vendors

Table 10. Standardized Score Regression Results for Digital Math Users (All Vendors) and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.423	0.003	15828.748	<.001
Years of use	-0.036	0.002	272.203	<.001
Software user	0.040	0.004	97.027	<.001
Gender – Male	-0.023	0.003	72.595	<.001
Black/African American	-0.685	0.012	3243.132	<.001
American Indian	-0.478	0.012	1549.326	<.001
Asian	0.060	0.011	30.694	<.001
Hispanic/Latino	-0.445	0.004	12137.640	<.001
Multiple Races	-0.086	0.009	93.258	<.001
Pacific Islander	-0.316	0.010	906.969	<.001
Low Income	-0.319	0.003	10059.242	<.001
Mobile	-0.244	0.006	1796.459	<.001
Rural	0.028	0.004	44.069	<.001
Chronically Absent	-0.344	0.005	5746.692	<.001
Free and Reduced Lunch	-0.003	0.000	1752.894	<.001
Mobile (school)	-0.013	0.000	1240.132	<.001
Chronically Absent (school)	0.002	0.000	25.147	<.001

Data sources: USBE and Digital Math Software Vendors

Table 11. SGP Regression Results for Digital Math Users (All Vendors) and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	53.263	0.118	202719.757	<.001
Years of use	-0.742	0.121	37.498	<.001
Software user	1.726	0.197	76.911	<.001
Gender – Male	-1.715	0.087	388.548	<.001
Black/African American	-3.726	0.380	95.973	<.001
American Indian	0.691	0.409	2.861	.091
Asian	4.450	0.352	160.204	<.001
Hispanic/Latino	-2.215	0.130	288.570	<.001
Multiple Races	-0.034	0.303	0.013	.911
Pacific Islander	-0.157	0.358	0.191	.662
Low Income	-1.902	0.106	320.654	<.001
Mobile	-3.584	0.245	214.779	<.001
Rural	0.964	0.144	45.074	<.001
Chronically Absent	-5.645	0.162	1212.652	<.001
Low Income (school)	-0.028	0.003	104.266	<.001
Mobile (school)	-0.249	0.016	244.647	<.001
Chronically Absent (school)	0.155	0.010	234.853	<.001

Data sources: USBE and Digital Math Software Vendors

Appendix C. Vendor Specific Regression Results For Digital Math Software Users and Non-Users

ALEKS

Table 12. Probability of Proficiency Regression Results for ALEKS Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.270	0.006	1869.752	<.001	1.311	.567
Years of use	-0.140	0.007	349.178	<.001	0.870	.465
Software user	0.004	0.012	0.107	0.707	1.004	.501
Gender – Male	0.028	0.007	15.618	<.001	1.028	.507
Black/African American	-1.457	0.043	1154.697	<.001	0.233	.189
American Indian	-1.166	0.040	836.910	<.001	0.312	.238
Asian	0.027	0.029	0.887	0.346	1.028	.507
Hispanic/Latino	-1.045	0.012	7982.371	<.001	0.352	.260
Multiple Races	-0.206	0.023	77.901	<.001	0.814	.449
Pacific Islander	-0.916	0.036	654.497	<.001	0.400	.286
Free and Reduced Lunch	-0.645	0.008	6711.841	<.001	0.525	.344
Mobile	-0.533	0.017	979.690	<.001	0.587	.370
Rural	0.123	0.011	122.415	<.001	1.131	.531
Chronically Absent	-0.685	0.013	2730.966	<.001	0.504	.335

Data sources: USBE and Digital Math Software Vendors

Table 13. Standardized Score Regression Results for ALEKS Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.286	0.003	11532.363	<.001
Years of use	-0.050	0.003	342.680	<.001
Software user	0.037	0.005	60.501	<.001
Gender – Male	-0.038	0.003	145.613	<.001
Black/African American	-0.782	0.016	2393.942	<.001
American Indian	-0.549	0.015	1383.177	<.001
Asian	0.004	0.014	0.063	.802
Hispanic/Latino	-0.528	0.005	12170.283	<.001
Multiple Races	-0.116	0.011	113.459	<.001
Pacific Islander	-0.411	0.014	839.915	<.001
Free and Reduced Lunch	-0.360	0.004	10252.499	<.001
Mobile	-0.289	0.007	1607.998	<.001
Rural	0.054	0.005	128.325	<.001
Chronically Absent	-0.375	0.005	4670.919	<.001

Data sources: USBE and Digital Math Software Vendors

Table 14. SGP Regression Results for ALEKS Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	52.348	0.092	320374.698	<.001
Years of use	-1.000	0.145	47.727	<.001
Software user	2.471	0.226	119.946	<.001
Gender – Male	-1.996	0.101	386.634	<.001
Black/African American	-4.907	0.492	99.325	<.001
American Indian	0.778	0.484	2.588	.108
Asian	3.421	0.449	58.124	<.001
Hispanic/Latino	-2.920	0.152	366.613	<.001
Multiple Races	-0.421	0.360	1.369	.242
Pacific Islander	-2.338	0.472	24.496	<.001
Free and Reduced Lunch	-2.101	0.116	326.624	<.001
Mobile	-4.012	0.290	191.454	<.001
Rural	1.683	0.161	109.792	<.001
Chronically Absent	-5.797	0.191	923.902	<.001

Data sources: USBE and Digital Math Software Vendors

I-Ready

Table 15. Probability of Proficiency Regression Results for i-Ready Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.315	0.016	369.374	<.001	1.370	.578
Years of use	-0.019	0.024	0.606	0.436	0.981	.495
Software user	0.197	0.035	30.751	<.001	1.217	.549
Gender – Male	0.106	0.018	33.280	<.001	1.112	.527
Black/African American	-1.223	0.089	188.978	<.001	0.294	.227
American Indian	-1.008	0.116	75.902	<.001	0.365	.267
Asian	0.021	0.070	0.085	0.770	1.021	.505
Hispanic/Latino	-0.936	0.028	1109.424	<.001	0.392	.282
Multiple Races	-0.164	0.057	8.304	0.004	0.849	.459
Pacific Islander	-0.798	0.081	96.932	<.001	0.450	.310
Free and Reduced Lunch	-0.739	0.020	1314.997	<.001	0.478	.323
Mobile	-0.496	0.040	153.930	<.001	0.609	.379
Rural	0.027	0.028	0.928	0.335	1.027	.507
Chronically Absent	-0.479	0.030	262.953	<.001	0.619	.382

Data sources: USBE and Digital Math Software Vendors

Table 16. Standardized Score Regression Results for i-Ready Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.243	0.007	1133.008	<.001
Years of use	-0.006	0.008	0.599	.439
Software user	0.078	0.013	34.607	<.001
Gender – Male	0.022	0.008	6.492	0.011
Black/African American	-0.787	0.038	439.732	<.001
American Indian	-0.526	0.045	137.531	<.001
Asian	0.056	0.035	2.495	.114
Hispanic/Latino	-0.501	0.013	1584.794	<.001
Multiple Races	-0.075	0.027	7.711	.005
Pacific Islander	-0.390	0.035	126.553	<.001
Free and Reduced Lunch	-0.430	0.010	1932.482	<.001
Mobile	-0.262	0.017	230.679	<.001
Rural	0.077	0.012	40.786	<.001
Chronically Absent	-0.278	0.013	461.138	<.001

Data sources: USBE and Digital Math Software Vendors

Table 17. SGP Regression Results for i-Ready Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	53.242	0.262	41394.926	<.001
Years of use	0.406	0.521	0.607	.436
Software user	-0.501	0.769	0.424	.515
Gender – Male	-1.062	0.287	13.739	<.001
Black/African American	-3.768	1.182	10.155	.001
American Indian	-1.670	1.487	1.261	.261
Asian	5.042	1.176	18.376	<.001
Hispanic/Latino	-2.532	0.414	37.348	<.001
Multiple Races	0.429	0.960	0.200	.655
Pacific Islander	-1.751	1.165	2.261	.133
Free and Reduced Lunch	-3.109	0.326	91.053	<.001
Mobile	-5.730	0.707	65.706	<.001
Rural	-0.363	0.417	0.759	.384
Chronically Absent	-3.830	0.471	66.264	<.001

Data sources: USBE and Digital Math Software Vendors

ST Math

Table 18. Probability of Proficiency Regression Results for ST Math Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.358	0.013	799.671	<.001	1.430	.589
Years of use	-0.111	0.013	68.611	<.001	0.895	.472
Software user	0.394	0.023	282.635	<.001	1.483	.597
Gender – Male	0.111	0.014	64.596	<.001	1.117	.528
Black/African American	-1.124	0.049	532.874	<.001	0.325	.245
American Indian	-1.072	0.064	282.494	<.001	0.342	.255
Asian	-0.018	0.040	0.200	.655	0.982	.496
Hispanic/Latino	-0.853	0.019	2072.836	<.001	0.426	.299
Multiple Races	-0.008	0.042	0.035	.851	0.992	.498
Pacific Islander	-0.663	0.044	230.429	<.001	0.515	.340
Free and Reduced Lunch	-0.831	0.015	2983.237	<.001	0.436	.303
Mobile	-0.522	0.028	346.654	<.001	0.593	.372
Rural	-0.353	0.038	87.217	<.001	0.703	.413
Chronically Absent	-0.577	0.024	574.262	<.001	0.562	.360

Data sources: USBE and Digital Math Software Vendors

Table 19. Standardized Score Regression Results for ST Math Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.300	0.005	3004.355	<.001
Years of use	-0.008	0.004	3.556	0.059
Software user	0.111	0.009	152.395	<.001
Gender – Male	0.003	0.006	0.268	0.604
Black/African American	-0.695	0.021	1092.595	<.001
American Indian	-0.576	0.024	578.382	<.001
Asian	-0.001	0.020	0.002	0.967
Hispanic/Latino	-0.445	0.008	2815.583	<.001
Multiple Races	0.000	0.020	0.000	0.994
Pacific Islander	-0.290	0.018	272.870	<.001
Free and Reduced Lunch	-0.483	0.007	4553.799	<.001
Mobile	-0.308	0.012	717.562	<.001
Rural	-0.178	0.016	126.819	<.001
Chronically Absent	-0.328	0.010	1091.104	<.001

Data sources: USBE and Digital Math Software Vendors

Table 20. SGP Regression Results for ST Math Users and Propensity-Score Matched Comparison Students

Feature	Estimate	Std err	Wald	*p*
(Intercept)	52.854	0.197	72008.003	<.001
Years of use	-1.038	0.260	15.874	<.001
Software user	3.012	0.488	38.029	<.001
Gender – Male	-0.932	0.209	19.885	<.001
Black/African American	-3.869	0.692	31.278	<.001
American Indian	-0.010	0.851	0.000	.991
Asian	4.175	0.647	41.673	<.001
Hispanic/Latino	-2.494	0.279	79.692	<.001
Multiple Races	1.111	0.695	2.557	.110
Pacific Islander	1.951	0.621	9.873	.002
Free and Reduced Lunch	-3.686	0.243	229.857	<.001
Mobile	-3.938	0.568	48.046	<.001
Rural	-0.846	0.537	2.481	.115
Chronically Absent	-4.662	0.377	152.582	<.001

Data sources: USBE and Digital Math Software Vendors

Appendix D. Regression Results for Digital Software Users Only

Table 21. Probability of Proficiency Regression Results for Digital Math Users Only (All Vendors)

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.481	0.019	614.651	<.001	1.617	0.618
Years of use	-0.138	0.006	548.902	<.001	0.871	0.465
Use 2nd quartile	0.139	0.011	154.734	<.001	1.149	0.535
Use 3rd quartile	0.256	0.011	506.322	<.001	1.291	0.564
Use 4th quartile	0.360	0.012	906.040	<.001	1.433	0.589
Coefficient of variation	-0.108	0.015	50.918	<.001	0.898	0.473
Gender – Male	0.030	0.010	8.058	<.01	1.030	0.507
Black/African American	-1.117	0.051	488.693	0	0.327	0.247
American Indian	-0.915	0.055	280.176	0	0.401	0.286
Asian	0.081	0.042	3.794	.051	1.085	0.520
Hispanic/Latino	-0.853	0.017	2546.151	<.001	0.426	0.299
Multiple Races	-0.141	0.035	16.491	<.001	0.869	0.465
Pacific Islander	-0.578	0.046	157.996	<.001	0.561	0.359
Free and Reduced Lunch	-0.492	0.011	1896.241	<.001	0.611	0.379
Mobile	-0.340	0.022	237.958	<.001	0.712	0.416
Rural	0.124	0.013	93.541	<.001	1.132	0.531
Chronically Absent	-0.444	0.016	757.570	<.001	0.641	0.391
Free and Reduced Lunch (school)	0.000	0.000	0.289	.591	1.000	0.500
Mobile (school)	-0.040	0.002	393.247	<.001	0.961	0.490
Chronically Absent (school)	-0.010	0.001	106.633	<.001	0.990	0.497

Data sources: USBE and Digital Math Software Vendors

Table 22. Standardized Score Regression Results for Digital Math Users Only (All Vendors)

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.315	0.008	1617.574	<.001
Years of use	-0.015	0.002	52.477	<.001
Use 2nd quartile	0.082	0.004	372.486	<.001
Use 3rd quartile	0.163	0.004	1410.912	<.001
Use 4th quartile	0.227	0.005	2482.406	<.001
Coefficient of variation	-0.051	0.006	78.658	<.001
Gender – Male	-0.029	0.005	37.935	<.001
Black/African American	-0.656	0.020	1034.358	<.001
American Indian	-0.423	0.021	404.159	<.001
Asian	0.048	0.020	5.587	.018
Hispanic/Latino	-0.427	0.007	3471.924	<.001
Multiple Races	-0.085	0.016	28.291	<.001
Pacific Islander	-0.273	0.019	203.763	<.001
Free and Reduced Lunch	-0.255	0.005	2679.427	<.001
Mobile	-0.177	0.009	394.542	<.001
Rural	0.066	0.005	146.309	<.001
Chronically Absent	-0.231	0.007	1241.774	<.001
Free and Reduced Lunch (school)	-0.001	0.000	30.042	<.001
Mobile (school)	-0.021	0.001	631.233	<.001
Chronically Absent (school)	-0.005	0.000	155.034	<.001

Data sources: USBE and Digital Math Software Vendors

Table 23. SGP Regression Results for Digital Math Users Only (All Vendors)

Feature	Estimate	Std err	Wald	*p*
(Intercept)	55.144	0.322	29281.489	<.001
Years of use	-1.214	0.114	114.076	<.001
Use 2nd quartile	2.878	0.200	206.293	<.001
Use 3rd quartile	5.109	0.200	651.706	<.001
Use 4th quartile	7.449	0.202	1359.843	<.001
Coefficient of variation	-1.875	0.270	48.273	<.001
Gender – Male	-2.080	0.138	227.505	<.001
Black/African American	-3.183	0.616	26.728	<.001
American Indian	1.143	0.677	2.852	.091
Asian	4.961	0.604	67.510	<.001
Hispanic/Latino	-1.573	0.213	54.629	<.001
Multiple Races	-0.318	0.500	0.404	.525
Pacific Islander	1.114	0.614	3.297	.069
Free and Reduced Lunch	-1.958	0.165	141.175	<.001
Mobile	-2.608	0.437	35.645	<.001
Rural	1.185	0.181	43.067	<.001
Chronically Absent	-4.924	0.260	359.736	<.001
Free and Reduced Lunch (school)	-0.017	0.005	13.369	<.001
Mobile (school)	-0.379	0.030	156.232	<.001
Chronically Absent (school)	-0.026	0.014	3.613	.057

Data sources: USBE and Digital Math Software Vendors

Appendix E. Vendor Specific Regression Results For Digital Math Software Users Only

ALEKS

Table 24. Probability of Proficiency Regression Results for ALEKS Users Only

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.513	0.024	448.893	<.001	1.671	.626
Years of use	-0.173	0.007	594.580	<.001	0.841	.457
Use 2nd quartile	0.153	0.014	125.138	<.001	1.165	.538
Use 3rd quartile	0.291	0.014	436.180	<.001	1.338	.572
Use 4th quartile	0.385	0.015	680.725	<.001	1.469	.595
Coefficient of variation	-0.087	0.019	21.906	<.001	0.917	.478
Gender – Male	-0.006	0.013	0.214	0.644	0.994	.499
Black/African American	-1.489	0.082	333.115	<.001	0.226	.184
American Indian	-1.018	0.069	215.420	<.001	0.361	.265
Asian	-0.011	0.059	0.037	0.848	0.989	.497
Hispanic/Latino	-1.018	0.023	2032.952	<.001	0.361	.265
Multiple Races	-0.278	0.044	39.132	<.001	0.758	.431
Pacific Islander	-0.790	0.067	140.923	<.001	0.454	.312
Free and Reduced Lunch	-0.466	0.014	1175.549	<.001	0.628	.386
Mobile	-0.344	0.029	141.339	<.001	0.709	.415
Rural	0.217	0.015	206.212	<.001	1.242	.554
Chronically Absent	-0.510	0.021	608.834	<.001	0.601	.375
Free and Reduced Lunch (school)	-0.002	0.000	27.218	<.001	0.998	.499
Mobile (school)	-0.052	0.003	245.868	<.001	0.949	.487
Chronically Absent (school)	-0.011	0.001	88.129	<.001	0.989	.497

Data sources: USBE and Digital Math Software Vendors

Table 25. Standardized Score Regression Results for ALEKS Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.329	0.010	1154.307	<.001
Years of use	-0.042	0.003	267.481	<.001
Use 2nd quartile	0.099	0.005	345.699	<.001
Use 3rd quartile	0.195	0.005	1290.850	<.001
Use 4th quartile	0.262	0.006	2100.455	<.001
Coefficient of variation	-0.034	0.007	22.330	<.001
Gender – Male	-0.051	0.006	81.688	<.001
Black/African American	-0.790	0.029	763.516	<.001
American Indian	-0.435	0.025	293.330	<.001
Asian	-0.026	0.028	0.844	.358
Hispanic/Latino	-0.493	0.009	2997.694	<.001
Multiple Races	-0.160	0.020	63.008	<.001
Pacific Islander	-0.361	0.027	179.547	<.001
Free and Reduced Lunch	-0.237	0.006	1652.244	<.001
Mobile	-0.169	0.012	208.777	<.001
Rural	0.096	0.006	226.322	<.001
Chronically Absent	-0.255	0.008	929.174	<.001
Free and Reduced Lunch (school)	-0.002	0.000	151.155	<.001
Mobile (school)	-0.019	0.001	318.689	<.001
Chronically Absent (school)	-0.004	0.001	74.253	<.001

Data sources: USBE and Digital Math Software Vendors

Table 26. SGP Regression Results for ALEKS Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	55.857	0.383	21272.114	<.001
Years of use	-1.661	0.135	152.254	<.001
Use 2nd quartile	3.158	0.233	183.334	<.001
Use 3rd quartile	5.836	0.233	625.282	<.001
Use 4th quartile	8.113	0.236	1177.467	<.001
Coefficient of variation	-2.325	0.318	53.479	<.001
Gender – Male	-2.450	0.160	235.632	<.001
Black/African American	-4.400	0.805	29.865	<.001
American Indian	1.398	0.800	3.056	.080
Asian	3.606	0.785	21.117	<.001
Hispanic/Latino	-2.025	0.253	63.930	<.001
Multiple Races	-1.268	0.590	4.624	.032
Pacific Islander	-2.125	0.822	6.687	.010
Free and Reduced Lunch	-1.550	0.189	67.411	<.001
Mobile	-2.532	0.530	22.839	<.001
Rural	2.713	0.207	172.096	<.001
Chronically Absent	-5.390	0.312	298.386	<.001
Free and Reduced Lunch (school)	-0.061	0.006	116.801	<.001
Mobile (school)	-0.292	0.042	48.364	<.001
Chronically Absent (school)	0.052	0.016	10.093	.001

Data sources: USBE and Digital Math Software Vendors

I-Ready

Table 27. Probability of Proficiency Regression Results for i-Ready Users Only

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	0.490	0.064	58.845	<.001	1.632	.620
Years of use	0.031	0.021	2.248	.134	1.031	.508
Use 2nd quartile	0.267	0.033	64.619	<.001	1.306	.566
Use 3rd quartile	0.403	0.035	133.975	<.001	1.496	.599
Use 4th quartile	0.598	0.037	256.565	<.001	1.819	.645
Coefficient of variation	-0.003	0.062	0.002	.960	0.997	.499
Gender – Male	0.115	0.029	15.165	<.001	1.122	.529
Black/African American	-0.977	0.145	45.454	<.001	0.377	.274
American Indian	-0.653	0.162	16.291	<.001	0.520	.342
Asian	0.177	0.137	1.660	.198	1.193	.544
Hispanic/Latino	-0.711	0.043	279.556	<.001	0.491	.329
Multiple Races	-0.097	0.094	1.054	.305	0.908	.476
Pacific Islander	-0.620	0.151	16.935	<.001	0.538	.350
Free and Reduced Lunch	-0.579	0.034	283.448	<.001	0.560	.359
Mobile	-0.297	0.055	29.140	<.001	0.743	.426
Rural	-0.036	0.035	1.048	.306	0.965	.491
Chronically Absent	-0.335	0.040	70.756	<.001	0.716	.417
Free and Reduced Lunch (school)	0.004	0.001	21.019	<.001	1.004	.501
Mobile (school)	-0.069	0.004	307.480	<.001	0.933	.483
Chronically Absent (school)	-0.017	0.003	41.037	<.001	0.983	.496

Data sources: USBE and Digital Math Software Vendors

Table 28. Standardized Score Regression Results for i-Ready Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.267	0.025	114.767	<.001
Years of use	0.069	0.006	121.434	<.001
Use 2nd quartile	0.111	0.012	85.550	<.001
Use 3rd quartile	0.224	0.013	314.550	<.001
Use 4th quartile	0.314	0.014	539.720	<.001
Coefficient of variation	0.023	0.022	1.005	.316
Gender – Male	0.035	0.013	7.061	<.001
Black/African American	-0.550	0.059	87.556	<.001
American Indian	-0.345	0.066	26.946	<.001
Asian	0.071	0.062	1.312	.252
Hispanic/Latino	-0.368	0.019	372.641	<.001
Multiple Races	-0.036	0.042	0.750	.386
Pacific Islander	-0.303	0.066	21.156	<.001
Free and Reduced Lunch	-0.298	0.014	427.028	<.001
Mobile	-0.139	0.021	43.499	<.001
Rural	0.070	0.014	23.533	<.001
Chronically Absent	-0.180	0.016	134.246	<.001
Free and Reduced Lunch (school)	0.001	0.000	9.244	.002
Mobile (school)	-0.033	0.002	350.053	<.001
Chronically Absent (school)	-0.013	0.001	118.228	<.001

Data sources: USBE and Digital Math Software Vendors

Table 29. SGP Regression Results for i-Ready Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	55.567	1.201	2140.022	<.001
Years of use	0.781	0.450	3.016	.082
Use 2nd quartile	3.296	0.633	27.139	<.001
Use 3rd quartile	4.986	0.653	58.212	<.001
Use 4th quartile	9.451	0.672	197.778	<.001
Coefficient of variation	0.944	1.150	0.673	.412
Gender – Male	-1.714	0.431	15.832	<.001
Black/African American	-1.027	1.886	0.296	.586
American Indian	0.257	2.260	0.013	.909
Asian	5.035	2.187	5.299	.021
Hispanic/Latino	-0.571	0.628	0.828	.363
Multiple Races	1.963	1.489	1.739	.187
Pacific Islander	0.701	2.029	0.119	.730
Free and Reduced Lunch	-2.992	0.533	31.525	<.001
Mobile	-0.846	1.091	0.602	.438
Rural	-3.226	0.531	36.916	<.001
Chronically Absent	-3.126	0.684	20.879	<.001
Free and Reduced Lunch (school)	0.021	0.012	2.979	.084
Mobile (school)	-0.818	0.064	163.849	<.001
Chronically Absent (school)	-0.276	0.042	42.527	<.001

Data sources: USBE and Digital Math Software Vendors

ST Math

Table 30. Probability of Proficiency Regression Results for ST Math Users Only

Feature	Estimate	Std err	Wald	*p*	Odds Ratio	Probability
(Intercept)	1.069	0.047	514.063	<.001	2.913	.744
Years of use	-0.091	0.013	46.815	<.001	0.913	.477
Use 2nd quartile	0.080	0.027	9.046	.003	1.083	.520
Use 3rd quartile	0.129	0.027	23.246	<.001	1.137	.532
Use 4th quartile	0.285	0.028	103.595	<.001	1.329	.571
Coefficient of variation	-0.180	0.032	31.169	<.001	0.835	.455
Gender – Male	0.107	0.026	17.434	<.001	1.113	.527
Black/African American	-0.851	0.076	126.372	<.001	0.427	.299
American Indian	-0.510	0.113	20.264	<.001	0.601	.375
Asian	0.085	0.070	1.450	.228	1.088	.521
Hispanic/Latino	-0.579	0.036	257.203	<.001	0.560	.359
Multiple Races	0.203	0.075	7.277	.007	1.225	.551
Pacific Islander	-0.398	0.074	29.217	<.001	0.672	.402
Free and Reduced Lunch	-0.595	0.029	416.248	<.001	0.552	.356
Mobile	-0.360	0.046	61.361	<.001	0.697	.411
Rural	-0.696	0.049	203.234	<.001	0.498	.333
Chronically Absent	-0.431	0.037	134.871	<.001	0.650	.394
Free and Reduced Lunch (school)	-0.002	0.001	7.546	.006	0.998	.499
Mobile (school)	-0.061	0.006	102.248	<.001	0.941	.485

Data sources: USBE and Digital Math Software Vendors

Table 31. Standardized Score Regression Results for ST Math Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	0.564	0.018	1010.086	<.001
Years of use	0.019	0.004	20.070	<.001
Use 2nd quartile	0.040	0.009	20.771	<.001
Use 3rd quartile	0.069	0.009	56.468	<.001
Use 4th quartile	0.128	0.010	176.401	<.001
Coefficient of variation	-0.076	0.011	46.625	<.001
Gender – Male	0.009	0.011	0.586	.444
Black/African American	-0.517	0.033	242.828	<.001
American Indian	-0.271	0.046	34.684	<.001
Asian	0.111	0.032	11.957	.001
Hispanic/Latino	-0.275	0.016	291.287	<.001
Multiple Races	0.086	0.034	6.500	.011
Pacific Islander	-0.166	0.030	31.229	<.001
Free and Reduced Lunch	-0.303	0.012	590.054	<.001
Mobile	-0.199	0.018	128.592	<.001
Rural	-0.283	0.021	189.331	<.001
Chronically Absent	-0.203	0.014	209.056	<.001
Free and Reduced Lunch (school)	-0.001	0.000	12.909	<.001
Mobile (school)	-0.034	0.002	225.196	<.001
Chronically Absent (school)	-0.006	0.001	20.713	<.001

Data sources: USBE and Digital Math Software Vendors

Table 32. SGP Regression Results for ST Math Users Only

Feature	Estimate	Std err	Wald	*p*
(Intercept)	54.017	0.860	3946.022	<.001
Years of use	-0.606	0.263	5.314	.021
Use 2nd quartile	1.841	0.530	12.073	.001
Use 3rd quartile	3.119	0.530	34.591	<.001
Use 4th quartile	5.435	0.543	100.299	<.001
Coefficient of variation	-1.431	0.648	4.876	.027
Gender – Male	-0.586	0.371	2.493	.114
Black/African American	-2.131	1.111	3.681	.055
American Indian	2.549	1.636	2.428	.119
Asian	6.791	1.073	40.081	<.001
Hispanic/Latino	-0.471	0.524	0.805	.370
Multiple Races	1.735	1.242	1.951	.162
Pacific Islander	5.084	1.036	24.095	<.001
Free and Reduced Lunch	-3.283	0.462	50.377	<.001
Mobile	-3.493	1.137	9.443	.002
Rural	-5.117	0.682	56.239	<.001
Chronically Absent	-4.091	0.657	38.790	<.001
Free and Reduced Lunch (school)	0.030	0.012	6.300	.012
Mobile (school)	-0.454	0.083	29.599	<.001
Chronically Absent (school)	-0.041	0.043	0.920	.337

Data sources: USBE and Digital Math Software Vendors