



Math Personalized Learning Software:
Examining Usage and Associations with Achievement in Utah
During the Covid-19 Pandemic

June 2022



Bridging Research, Policy, and Practice

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Executive Summary

The purpose of the current study was to examine the degree to which math personalized learning software use changed over the course of the Covid-19 pandemic and to determine whether usage or the benefits of usage differed across groups. The focus of the study is on students who are low-income (i.e., students who are eligible for free- or reduced-price lunch) and schools that are low-income (i.e., schools in which 40% or more of students are eligible for free- or reduced-price lunch) given clear evidence both nationally and in Utah that the pandemic differentially impacted students who were economically marginalized, a group that was already struggling academically. Key findings related to three central research questions are summarized here. Detailed findings follow.

Were levels of software usage from 2017-2018 to 2020-2021 related to low-income status at either the student or school level?

Students who were low-income used math personalized learning software for less time than students who were not low-income. The magnitude of the gap in usage by student low-income status was modest, ranging from 6 minutes to 22 minutes per month across years and vendors where the median monthly usage was between 1 and 3 hours. The relationship between math personalized learning software use and low-income status at the school level was highly variable across years and vendors. However, students who were low-income used math personalized learning software for less time than students who were not low-income at schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income.

Were levels of software usage just prior to and after the soft closure of Utah's schools in March 2020 related to low-income status at either the student or school level?

Students who were low-income used math personalized learning software for less time than students who were not low-income during these months, with the largest gaps emerging in April 2020, after the soft closure of Utah's schools. The magnitude of the gap in usage in April 2020 by student low-income status was modest, ranging from 8 minutes to 36 minutes across vendors. Students who were low-income used math personalized learning software for less time in April 2020 than other students at schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income. Students in schools with a higher percentage of students who were low-income (i.e., \geq 40%) generally used math personalized learning software for less time than students in schools with a lower percentage of students who were low-income (i.e., < 40%) in April 2020. However, differences in usage by low-income status at the school level were statistically significant for only one vendor after controlling for the effects of student low-income status.

What was the relationship between software usage and student math achievement in 2020-2021, the first full academic year following the soft closure of Utah's schools in March 2020 and a year during which many students experienced disrupted learning?

Student use of math personalized learning software was positively related to growth in mathematics for most vendors, with some evidence for diminishing returns at high usage levels for some vendors. For the three vendors for which the relationship was most clearly linear, SGPs increased by between 3.91 and 5.56 points for every hour increase in mean monthly usage. The benefits of math personalized learning software were similar for students attending schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income and, generally, for both students who were low-income and other students. When differences emerged, the benefits were stronger for students who were low-income.

The findings of the current study have implications for understanding the degree to which math personalized learning software is accessible, can be used successfully in remote, hybrid, or disrupted

learning environments, and might contribute to Covid-19 learning recovery efforts. Much more work is needed to understand how math personalized learning software is being implemented in Utah's classrooms and to identify the specific implementation practices that are most clearly associated with positive teacher and student perceptions of the software and with positive student mathematics attitudes and achievement for different learners in different contexts.

Overview

Disrupted Learning During the Covid-19 Pandemic

On March 13, 2020, Utah’s Governor announced a two-week “soft closure” of all public schools in the state to begin on March 16. Teachers were allotted two professional days to prepare to transition from in-person to remote instruction on March 18 (Scheffler, 2020). A month later, on April 14, 2020, the Governor announced that the soft-closure would be extended to the end of the academic year (*Governor Herbert Announces Extension “Soft Closure” for Public Schools | Coronavirus*, n.d.).

Despite an anticipated return to in-person learning in Fall 2020, the pandemic resulted in myriad models of instruction (e.g., in-person, virtual, and hybrid – some days in-person and some days remote) being implemented across Utah during the 2020-2021 academic year. Data collected in June 2021 by the Utah State Board of Education (USBE) to assess the primary learning model adopted by schools indicated that, during the 2020-2021 academic year, 31% of Utah’s 1,050 schools offered regular in-person instruction, 5% offered remote instruction, and 62% offered a blend of in-person and remote instruction as their primary learning model. Temporary closures triggered by Covid-19 cases and quarantines designed to mitigate pandemic risk resulted in additional disruptions to typical school operations for many students (USBE and the National Center for the Improvement of Educational Assessment, Inc., 2021).

The Impact of the Covid-19 Pandemic on Student Outcomes

Pandemic-related learning disruptions were associated with substantial learning loss in mathematics, especially among students who were economically-marginalized.

Consistent with national trends (see Goldhaber, Kane, McEachin, Morton, Patterson, & Staiger, 2022, Hammerstein, König, Dreisörner, & Frey, 2021, and Lewis & Kuhfeld, 2021 for reviews), a report released by the USBE in October 2021 suggests that pandemic-related learning disruptions were associated with substantial learning loss. Analyses of student RISE and Utah Aspire Plus assessments revealed that scores were lower in 2020-2021 than in 2018-2019 at all grade levels (i.e., Grades 5 – 10) and all content areas (i.e., English and language arts, math, and science) examined in the report (USBE and the National Center for the Improvement of Educational Assessment, Inc., 2021).¹

Some of the largest differences in academic achievement scores between years appeared on math assessments and among students who were economically marginalized.² In 2020-2021, only 25.5% of students who were economically marginalized were proficient in math compared to 41.9% of all students. This finding is particularly sobering given the USBE’s goals for raising proficiency rates among groups who have been economically marginalized or historically-underperforming. The target proficiency rate

¹ RISE assessments were not administered in 2019-2020 because of the Covid-19 pandemic.

² In 2019, the American Psychological Association (APA) released a report reiterating its commitment to person-first (e.g., “individuals with low-income”) and culturally-sensitive language (e.g., “individuals who are economically marginalized”) to describe economically disenfranchised people. The report recommends the use of the term “economically marginalized” rather than “economically disadvantaged” to capture “the societal constructs that contribute to marginalization” (APA, 2019, p. 1). The UEPC strives to reflect these commitments in the current report. We use the term “economically marginalized” to reference findings from reports that have used similar terms (e.g., “economically disadvantaged”). We use the term “low-income” to reference findings from reports that have used similar terms (e.g., “lower-income” or “low-SES”). We also use the term “low income” when describing specific research questions or findings from the current study.

for students who are economically marginalized in math is 55.8% by 2021-2022 (USBE Strategic Plan, 2021 Implementation Update).

The Promise of Math Personalized Learning Software

A growing literature suggests that educational technology – including personalized learning software – has the potential to improve student learning outcomes in mathematics (see Cheung & Slavin, 2013, Hillmayr, Ziernwald, Reinhold, Hofer, & Reiss, 2020, and Young, Gorumek, & Hamilton, 2018, for meta-analytic reviews). Consistent with this perspective, research conducted by the Utah Education Policy Center (UEPC) for Utah’s STEM Action Center³ has demonstrated that students who use personalized learning software provided through STEM Action Center’s K-12 Math Personalized Learning Software Grant program⁴ are more likely to be proficient in and to demonstrate growth in mathematics than non-users, especially when usage levels are relatively high (e.g., Su, Rorrer, Owens, Pecsok, Moore, & Ni, 2020). It is unclear whether personalized learning software use mitigated learning loss during the pandemic, but some emerging evidence is consistent with this possibility (Meeter, 2021; Spitzer & Musslick, 2021).

Disparities in Math Software Usage and Achievement by Low-Income Status

Although there is ample evidence for a “digital divide” that was exacerbated during the pandemic as students moved to remote or hybrid instruction (Ong, 2020), it is unclear if and how disparities in access to technology in Utah – including access to mobile computing devices and reliable internet – are reflected in student use of math personalized learning software.⁵ A recent study released by one math personalized learning software vendor suggests that the pandemic exacerbated existing inequalities (Rome & Lay, 2022).⁶ Although, for this vendor, usage was marginally *higher* among students in schools in lower-income communities than among students in schools in higher-income communities prior to the pandemic, this trend reversed post-pandemic. Beginning in March 2020 and continuing through the following academic year, usage rates were much *lower* among students in lower-income communities than among students in higher-income communities. More work is needed to determine whether this trend is consistent across vendors and to examine whether low-income status at the student level (i.e., whether a *student* is eligible for free or reduced-price lunch) or low-income status at the school level (i.e., whether a student attends a *school* where a high percentage of students are eligible for free or reduced-price lunch) plays the larger role in any disparities in usage.

More work is needed to understand whether students who are economically marginalized differ from other students in the amount of time they spend using math personalized learning software. Likewise, more work is needed to understand whether students who are economically marginalized are more, less, or equally likely to benefit from using math personalized learning software.

³ <https://stem.utah.gov>

⁴ <https://stem.utah.gov/educators/funding/k-12-math-personalized-learning-software-grant/>

⁵ Closing the digital divide has been a priority in Utah (Utah Education and Telehealth Network, 2020; Utah State Board of Education, 2020). Key goals of the [Utah Broadband Access Initiative](#) are to expand access to high-speed internet and mobile computing devices both in school and in homes and communities. Consistent with these goals, the percentage of students who attend school with some type of 1:1 mobile device program increased from 11% in 2015 to 30% in 2019 and the percentage of schools that offer the fastest Wi-Fi access currently available increased from 36% in 2015 to 95% in 2019 (Utah State Board of Education, 2020).

More work is also needed to understand whether low-income status moderates the overall positive relationship between software usage and achievement. In a recent meta-analysis, Cheung and Slavin (2013) presented findings indicating that the positive impact of educational technology use on the mathematics achievement of K-12 students did not differ by low-income status. However, the meta-analysis examined only income at the school level where low-income schools were defined as schools in which 40% or more of students in the school were eligible for free or reduced-priced lunch.

Implications for Informing Covid-19 Recovery Interventions

Given the outsized impact that the Covid-19 pandemic has had on learning outcomes for students who are economically marginalized both nationally and in Utah (Goldhaber et al., 2022; Lewis & Kuhfeld, 2021; Hammerstein et al., 2021), more work is needed to examine whether levels of math personalized software use or the relationship between math personalized software use and achievement differs by low-income status at either the student or school level. The findings will be important in informing decisions about Covid-19 recovery interventions.

If the benefits of software use are the same or stronger for students who are economically marginalized or for schools with high numbers of students who are economically marginalized, but usage is lower among these students or in these schools, it may indicate that additional efforts are needed to increase equitable access to math software.

If the benefits of software use are weaker for students who are economically marginalized or for schools with high numbers of students who are economically marginalized, it may indicate that efforts to change implementation practices may be an important precursor to Covid-19 recovery efforts that involve math personalized learning software.

The findings will be especially important given that math personalized learning software is often an important component of other interventions that have been lauded as having powerful potential for addressing historical and pandemic-related learning disparities (Goldhaber et al., 2022; Hanover Research, 2020; Nickow, Oreopoulos, & Quan, 2020). These interventions include high-dosage tutoring and extending learning time initiatives (e.g., “double-dose math”).

The Current Study

The current study aims to contribute to the existing research literature and to inform policy and practice in Utah by addressing three sets of research questions.

1. Did math personalized learning software usage change year-over-year from 2017-2018 (pre-pandemic) through 2020-2021? Were levels of usage related to low-income status at either the student or school level?
2. Did math personalized learning software usage change month-over-month from February 2020 to April 2020 as students in Utah moved to remote instruction because of the pandemic? Were changes in usage related to low-income status at either the student or school level?

3. What was the relationship between math personalized learning software usage and achievement in 2020-2021 (i.e., in the year following the soft closure of Utah schools)? Was the relationship between usage and math achievement moderated by low-income status at either the student or school level?

The analyses presented in this UEPC report yield insights into the degree to which math personalized learning software use changed over the course of the Covid-19 pandemic and whether usage or the benefits of usage differed across groups. The findings are important in understanding the degree to which math personalized learning software is accessible, can be used successfully in remote, hybrid, or disrupted learning environments, and has the potential to contribute to Covid-19 learning recovery efforts.

Methods

This study is one in a series of studies conducted by the Utah Education Policy Center (UEPC) as part of the K-12 Math Personalized Learning Software Grant Program offered by Utah's STEM Action Center (e.g., Owen, Rorrer, Ni, Onuma, Pecsok, & Moore, 2020; Su et al., 2020).⁷ This grant provides funding to Utah schools and districts to purchase licenses for math personalized learning software from approved vendors. Vendors are approved based on rigorous evaluation studies.

Data Sources

The data used for this study came from two sources. First, using a secure platform, each of six approved STEM Action Center vendors provided student software usage data to the UEPC. Four of these vendors – ALEKS, i-Ready, Mathspace, and ST Math – provided data for all four academic years (i.e., 2017-2018 to 2020-2021) that were the focus of this study. Two vendors – DreamBox and Imagine Math – provided data for only three academic years (i.e., 2018-2019 to 2020-2021) as these vendors were not on the approved vendor list for the STEM Action Center prior to the 2018-2019 academic year. Second, student demographic data and student achievement data from annual standardized mathematics assessments were utilized via a Data Sharing Agreement with the Utah State Board of Education (USBE).⁸

Data Types

Educational and demographic data included in the current study were six student-level variables (i.e., grade level, race/ethnicity, mobility status (i.e., changing schools within the school year), special education status, low-income status, and limited English status) and one school-level variable (% of students who were low-income). Grade-level is a categorical variable ranging from 0 (Kindergarten) to 12 (12th grade). All other student-level variables are dichotomous (e.g., Asian or not Asian, mobile or not mobile). Students identified as low-income are students who were deemed eligible for free or reduced-price lunch. In initial analyses, we examined low-income at the school level as both a continuous variable (i.e., with 0% to 100% of students eligible for free or reduced-price lunch) and as a categorical variable (i.e., 40% or more of students eligible for free or reduced-price lunch vs. less than 40% of students eligible for free or reduced-price lunch). To ease interpretations, to simplify visualizations, and to align with prior work examining the degree to which economic marginalization moderates the impact of math software on student achievement (e.g., Cheung & Slavin, 2013; Rome & Lay, 2022), all analyses presented in this report treat low-income at the school level as a categorical variable.

Math personalized learning software usage data were provided by six vendors – ALEKS, DreamBox, i-Ready, Imagine Math, Mathspace, and ST Math – as number of minutes of use by each student per month.

Achievement data included 2017-2018 SAGE and 2018-2019 and 2020-2021 RISE student growth percentile (SGP) scores. RISE assessments were not administered in 2019-2020 because of the pandemic. SGP is a continuous variable that indicates the level of student growth or improvement from the previous

⁷ <https://stem.utah.gov/educators/opportunities/k-12-math-personalized-learning-software-grant/>

⁸ The Utah Education Policy Center has a Master Data Sharing Agreement with the Utah State Board of Education for use of education data for evaluation and research purposes. The UEPC adheres to terms of the Master Data Sharing Agreement, including terms of use, confidentiality and non-disclosure, data security, monitoring, and applicable laws. The UEPC also complies with University of Utah Institutional Review Board policies for educational research and evaluation. Though UEPC is housed at the University of Utah, only authorized UEPC staff may access the data, and data are not available throughout the University or to other parties. The views expressed in this report are those of UEPC staff and do not necessarily reflect the views or positions of the USBE or the University of Utah.

year relative to peers. SGP scores can range from 1 (lowest growth) to 99 (highest growth). For example, an SGP score of 52 indicates that the student showed more growth or greater improvement than 52% of other students who performed similarly the previous year.

Data Analyses

This study included descriptive statistics to summarize year-over-year usage data (i.e., number of hours/minutes used per month for each of four years) and month-over-month usage data (i.e., number of hours/minutes used per month from February 2020 to April 2020).

We used multilevel modeling (MLM) to a) compare levels of math personalized learning software usage by low-income status at both the student and school level and to b) explore associations between math personalized learning software usage and math achievement by low-income status at both the student and school level.⁹ Initial analyses explored other demographic and educational characteristics of students and schools. However, the focus of this report is on low-income status given clear evidence that the pandemic differentially impacted students who were economically marginalized, a group that was already struggling academically.

⁹ Multilevel models (also known as linear mixed models, hierarchical linear models, or mixed-effects models) are appropriate when data are organized into nested levels. In the current study, students (Level 1) are nested within schools (Level 2).

Results

A dataset was created by matching student software usage data from vendors to demographic, educational, and achievement data using several matching algorithms. Records were excluded from the dataset if student usage data could not be matched to demographic, educational, and achievement data or if student usage data indicated less than one minute of program use during the school year.

As shown in Table 1, match rates were greater than or equal to 90% across vendors and years.

Table 1. Match rate by vendor and year

Year	ALEKS	DreamBox	i-Ready	Imagine Math	Mathspace	ST Math
2017-2018	96%	–	97%	–	94%	93%
2018-2019	96%	97%	97%	96%	92%	93%
2019-2020	95%	98%	97%	97%	90%	94%
2020-2021	94%	97%	97%	96%	96%	97%

Note. DreamBox and Imagine Math were not approved vendors for STEM Action Center’s K-12 Math Personalized Learning Software Grant prior to the 2018-2019 academic year.

As shown in Table 2, the number of unique student users varied by vendor and year. Across the four years, ALEKS had the highest number of users, while DreamBox and Mathspace had the lowest. ST Math and Dreambox increased users between 2019-2020 and 2020-2021, with Dreambox adding over 15,000 users. During the same time period, ALEKS and Imagine Math experienced some reduction in the number of users.

Table 2. Number of unique student users by vendor and year

Year	ALEKS	DreamBox	i-Ready	Imagine Math	Mathspace	ST Math
2017-2018	76,437	–	26,470	–	6,704	34,294
2018-2019	86,679	2,128	42,092	34,489	3,463	48,515
2019-2020	75,400	2,036	46,593	50,621	9,644	52,708
2020-2021	65,638	17,983	47,607	38,160	9,367	59,572

As shown in Table 3, some student educational and demographic characteristics differed substantially across vendors. For example, ALEKS was used primarily by students in late elementary school through high school (i.e., 5th grade through 10th grade). This is in sharp contrast with ST Math, which was used primarily by students in elementary school (i.e., kindergarten through 5th grade). The percent of students who were identified as low-income by virtue of being eligible for free or reduced-price lunch also varied considerably across vendors, from 28% among students using Imagine Math to 48% of students using ST Math.¹⁰ ST Math also had the highest percentage of students who identified as Asian, Black, Hispanic, and Pacific Islander and who were identified as having limited English proficiency.

¹⁰ For comparison, for the four academic years included in the current study, the percent of Utah students who were identified as low-income was 35% in 2017-2108, 33% in 2018-2019, 33% in 2019-2020, and 30% in 2020-2021 (<https://www.schools.utah.gov/data/reports?mid=1424&tid=4>).

Table 3. Student-level educational and demographic descriptive statistics by vendor

Vendor	Grade Percentiles			Race/Ethnicity						Other Demographics			
	10%	50%	90%	Asian	Black	Hispanic	Native American	Pacific Islander	White	Mobile	Special Ed	Low-Income	Limited English
ALEKS	5	8	10	2%	2%	17%	3%	2%	94%	12%	14%	36%	6%
DreamBox	K	3	7	3%	3%	21%	2%	3%	92%	13%	15%	39%	13%
i-Ready	1	3	6	3%	3%	20%	2%	2%	93%	13%	16%	40%	10%
Imagine Math	1	4	7	3%	3%	15%	2%	2%	94%	10%	15%	28%	7%
Mathspace	4	7	10	3%	3%	17%	3%	2%	94%	10%	16%	36%	6%
ST Math	K	3	5	4%	5%	26%	3%	4%	87%	13%	15%	48%	20%



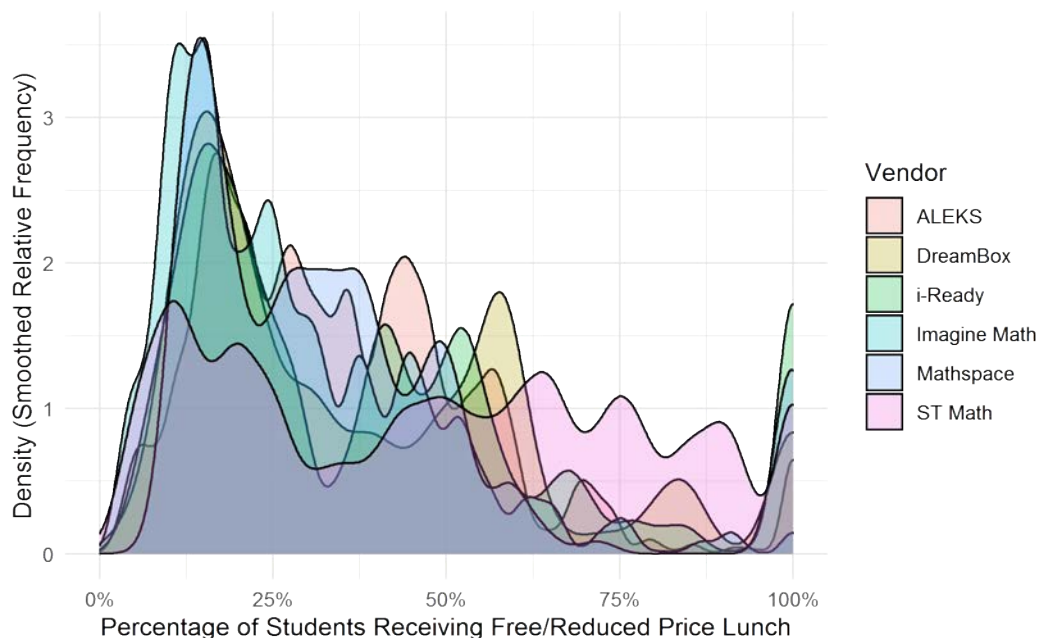
Note. **Grade percentiles** indicate the grade level that 10%, 50%, or 90% of software users were at or below. For example, for ALEKS, 10% of users were at grade 5 or below, 50% of users were at grade 8 or below, and 90% of users were at grade 10 or below.



Note. Students were identified as **low-income** if they were eligible for free or reduced-price lunch.

As shown in Figure 1, vendors also varied considerably in the percentage of their students who attended schools with a high percentage of students who were low income. The high peaks on the left side of the figure indicate a concentration of students who were in schools with less than 25% of students receiving free or reduced-price lunch. Few vendors included schools where more than 70% of students received free or reduced-price lunch. The exception was ST Math (represented in pink), where students were more evenly distributed across schools with varying percentages of students receiving free or reduced-price lunch.

Figure 1. Distribution of student users by the percentage of students at their school who were identified as low-income



Consistent with these data, the percentage of student software users who attended schools that were identified as low-income (by virtue of having 40% or more of students eligible for free or reduced-price lunch) ranged from 23% (for Imagine Math) to 58% (for ST Math).

Table 4. Percentage of student software users attending schools with 40% or more students receiving free or reduced-price lunch

Year	ALEKS	DreamBox	i-Ready	Imagine Math	Mathspace	ST Math
School low-income	38%	40%	44%	23%	31%	58%

Note. Schools are identified as **low-income** if the percentage of students at that school who were eligible for free or reduced-price lunch was 40% or higher.

Research Question Set #1

In our first set of analyses, we sought to examine whether a) math personalized learning software usage changed from 2017-2018 (pre-pandemic) to 2020-2021, b) whether levels of usage over this four-year period varied by low-income status at the student level, c) whether levels of usage over this four-year period varied by low-income status at the school level, and d) whether any gaps that emerged between students who were low-income and other students differed by the percentage of low-income students in the school.

We begin this section with a summary of key findings. In the pages that follow, we present detailed findings for Research Question Set #1.

Summary of Key Findings for Research Question Set #1.

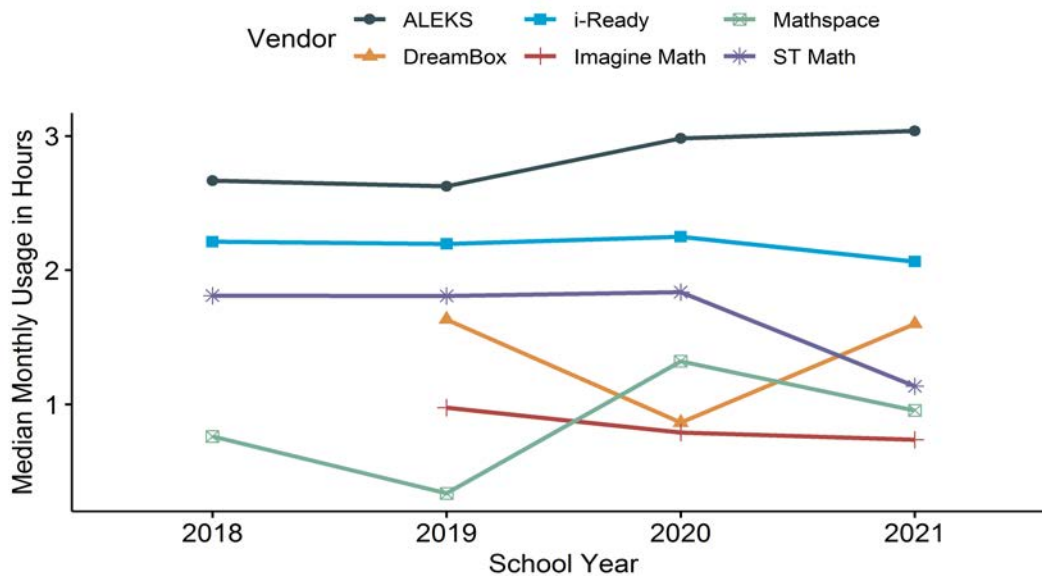
Were levels of software usage from 2017-2018 to 2020-2021 related to low-income status at either the student or school level?

Students who were low-income used math personalized learning software for less time than students who were not low-income. The magnitude of the gap in usage by student low-income status was modest, ranging from 6 minutes to 22 minutes per month across years and vendors. The relationship between math personalized learning software use and low-income status at the school level was highly variable across years and vendors. However, students who were low-income used math personalized learning software for less time than students who were not low-income at schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income.

1a | Did math personalized learning software usage change from 2017-2018 to 2020-2021?

To answer this question, we considered median software use. As shown in Figure 2, there was no consistent pattern of change in software usage across vendors for the four school years included in the current study.¹¹ Some vendors (i.e., ALEKS, Mathspace) showed a pattern of increased median monthly usage over time, while other vendors showed declines in usage (sometimes followed by increases in usage) over time.

Figure 2. Median math software usage (in hours per month) by year and vendor



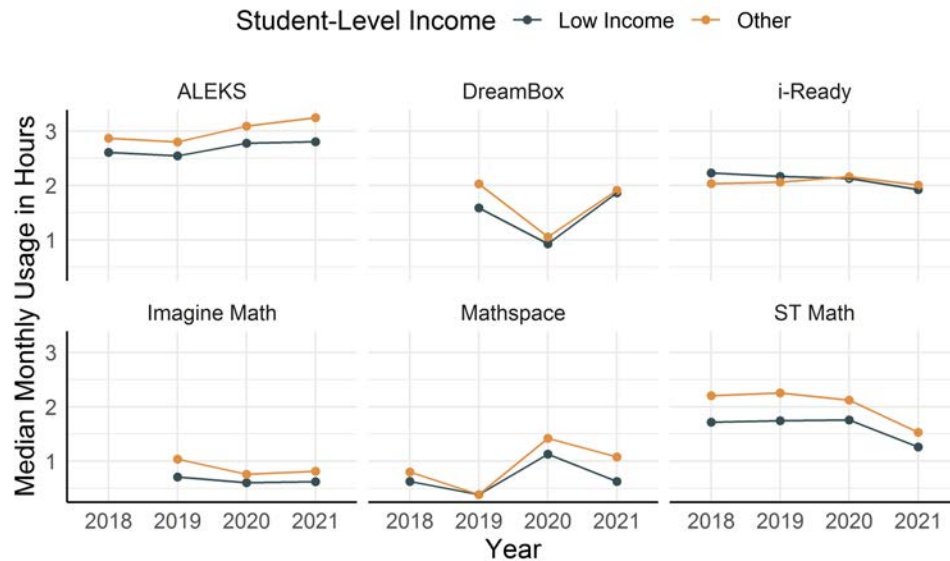
Note. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage.

1b | Were levels of usage related to student low-income status?

Clearer patterns in the data emerge when year-over-year usage is examined by student low-income status. As shown in Figure 2, student usage was generally lower for students who were low-income than for other students. The one exception to this general rule was for i-Ready users in 2018 and 2019 where the reverse was true: usage was higher for students who were low-income than for other students. For some vendors (e.g., ALEKS and Mathspace), the gap in usage between students who were low-income and other students appeared to widen in 2020-2021, after the soft closure of Utah schools in March 2020. For other vendors, this gap appeared to shrink (e.g., ST Math).

¹¹ In Figure 2, median monthly usage was computed by first computing the average monthly usage for each student, and then computing the median of those values within year and vendor. Thus, for each point in the graph, half of the students have an average monthly usage that is above that point and half of the students have an average monthly usage that is below that point. Median usage is reported rather than mean usage as the usage data are positively skewed, with a small percentage of students using math personalized learning software for more than ten hours per month (5% of ALEKS users, 2% of DreamBox users, and less than 1% of i-Ready, Imagine Math, Mathspace, and ST Math users). Extremely high usage was capped at 43 hours per month (2 hours per school day) because of analyses indicating that usage above that level was unlikely to be repeated, even among very high users.

Figure 3. Math software usage (in hours per month) by year, vendor, and student low-income status

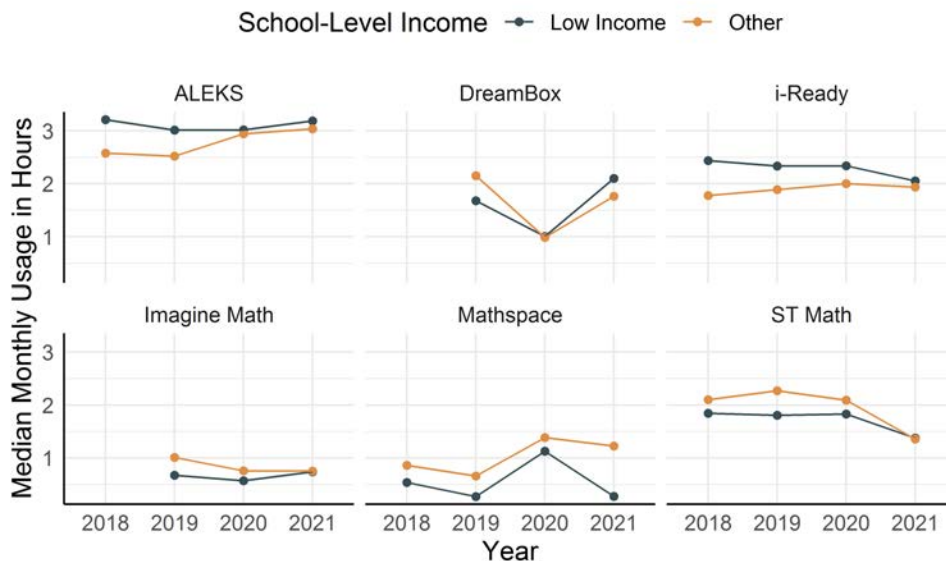


Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage.

1c | Were levels of usage related to percent of low-income students at the school?

The pattern of results for students attending schools with a high vs. low percentage of low-income students was inconsistent. As shown in Figure 4, for some vendors (e.g., Imagine Math, Mathspace, and ST Math) the pattern of findings was similar to the pattern found for student low-income status: usage was lower in low-income schools. For other vendors (e.g., Aleks and i-Ready), the reverse was true: usage was higher in low-income schools. DreamBox showed a mixed pattern.

Figure 4. Math software usage (in hours per month) by year, vendor, and school % low-income



Note. Schools are identified as **low-income** if 40% or more of students were eligible for free or reduced-price lunch. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage.

1d | Did students who were low-income have lower levels of usage across schools, or did the magnitude of the gap differ by the percentage of low-income students in the school?

Because a significant amount of the variation in software usage occurred across schools (ICCs = .22 to .45), multilevel modeling was used to examine the *independent* effects of low-income status at the student and school levels on math personalized software usage, and to examine whether the gap in usage between students who were identified as low-income and other students differed by the percentage of low-income students in the school.¹²

Table 5. Summary of multilevel model predicting year-over-year usage by vendor

Parameters	ALEKS	DreamBox	i-Ready	Imagine Math	Mathspace	ST Math
Regression coefficients (fixed effects)						
Intercept	3.26***	2.39***	2.18***	1.01***	1.10***	2.09***
Student Low-Income	-0.27***	-0.36***	-0.14***	-0.13***	-0.10**	-0.24***
School Low-Income	0.23***	2.12***	0.08***	0.12***	0.26***	-0.34***
Interaction	-0.03	-0.14	0.00	-0.02	0.03	0.03
Variance components (random effects)						
Residual	6.27	4.84	1.22	1.07	1.91	2.61
Intercept	3.61	5.40	0.43	0.42	1.17	0.75
Slope	0.09	0.20	0.02	0.01	0.03	0.02
Covariance	-0.21	-0.98	-0.03	-0.04	-0.05	-0.08

Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. Schools are identified as **low-income** if 40% or more of students were eligible for free or reduced-price lunch.

** $p < .01$. *** $p < .001$.

As shown in Table 5, estimates for the effect of low-income status at the student level on software usage (highlighted in orange) show that, across years and vendors, students who were low-income used math personalized software for fewer hours than other students. The gap in monthly usage ranged from 0.10 hours (= 6.13 minutes) to 0.36 hours (= 21.6 minutes) *less* per month for low-income students. These estimates controlled for the percentage of students who were low-income at the school level.

The valence and magnitude of estimates for the effect of low-income status at the school level on software usage (highlighted in green) were more mixed. The gap in monthly usage ranged from .34 hours (= 20.4 minutes) *less* to 2.12 hours (= 127.2 minutes) *more* per month more for students from low-income schools.¹³ These estimates controlled for low-income status at the student level.

¹² The ICC, or intraclass correlation, can be defined here as the proportion of software usage variation that occurs across schools or as the expected correlation between the software usage levels of two students from the same school. Multilevel modeling is not necessary when ICC values do not differ significantly from zero. Multilevel modeling is warranted, however, when ICCs are significantly greater than zero. Unlike Ordinary Least Squares (OLS) regression, multilevel modeling allows the researcher to model variance that occurs both across students and across schools.

¹³ The unusually large estimate for the effect of % low income at the school level for DreamBox is due in large part to large changes in mean usage across years (see Figure 2). When the data are disaggregated by year, the effect of school-level low income is much reduced: -0.55, -.12, and -0.13 for 2019, 2020, and 2021, respectively.

Estimates for the interaction between student-level low-income and % low-income at the school level (highlighted in gray) were not statistically significant, indicating that students who were low-income used the math personalized learning software for less time than students who were not low-income across schools, not just at schools with a high (or low) percentage of students who were low-income.

Research Question Set #2

In our second set of analyses, we sought to examine whether a) math personalized learning software usage changed month-over-month from February 2020 to April 2020 as students moved to remote instruction because of the Covid-19 pandemic, b) whether levels of usage over this three-month period varied by low-income status at the student level, c) whether levels of usage over this three-month period varied by low-income status at the school level, and d) whether any gap that might emerge between students who were low-income and other students in April 2020 (after the soft closure of Utah's schools) would differ by the percentage of low-income students in the school.

We begin this section with a summary of key findings. In the pages that follow, we present detailed findings for Research Question Set #2.

Summary of Findings for Research Question Set #2.

Were levels of software usage just prior to and after the soft closure of Utah's schools in March 2020 related to low-income status at either the student or school level?

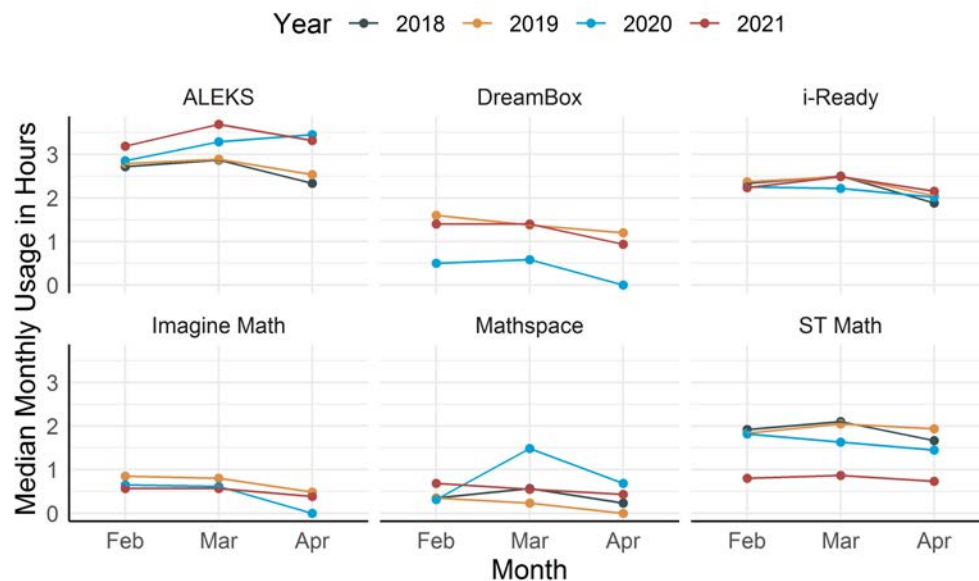
Students who were low-income used math personalized learning software for less time than students who were not low-income during these months, with the largest gaps emerging in April 2020. The magnitude of the gap in usage in April 2020 by student low-income status was modest, ranging from 8 minutes to 36 minutes across vendors. Students who were low-income used math personalized learning software for less time in April 2020 than other students at schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income.

Students in schools with a higher percentage of students who were low-income (i.e., \geq 40%) generally used math personalized learning software for less time than students in schools with a lower percentage of students who were low-income (i.e., < 40%) in April 2020. However, differences in usage by low-income status at the school level were statistically significant for only one vendor after controlling for the effects of student low-income status.

2a | Did math personalized learning software usage change from February 2020 to April 2020?

As shown by the blue lines in Figure 5 (representing 2020, the year when schools closed in March), there was no consistent pattern of change across vendors in month-to-month math personalized learning software usage during the three months that spanned the soft closure of Utah schools. Some vendors showed a pattern of increased median monthly usage over time from February 2020 to April 2020 (e.g., ALEKS), while other vendors showed declines in usage during this same period (e.g., ST Math). For some vendors, patterns largely mirrored patterns seen in other years (e.g., DreamBox), while the period of time in 2020 just prior to and after the initial COVID impact represented a somewhat unique pattern over these months for other vendors (e.g., ALEKS, Mathspace).¹⁴

Figure 5. Math software usage (in hours per month) by month, year, and vendor



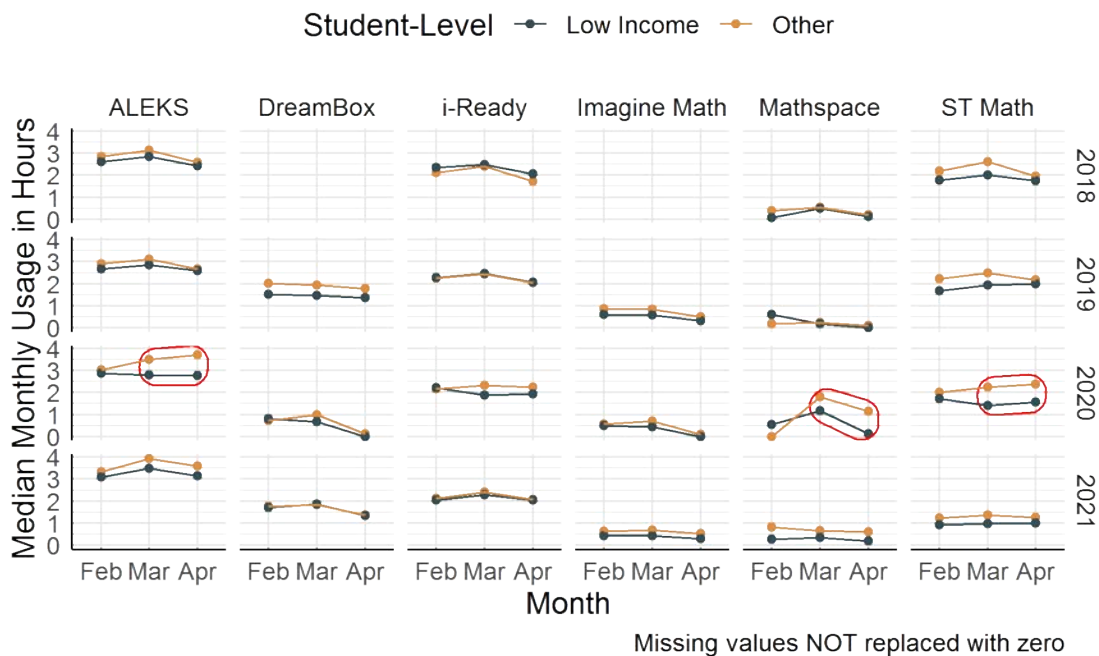
Note. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage.

2b | Were levels of usage from February 2020 to April 2020 related to student low-income status?

As shown in Figure 6, students who were low-income generally had lower math personalized learning software usage than other students. This is consistent with the year-over-year trends shown in Figure 3. Importantly, however, gaps in usage by low-income status were wider in March 2020 and April 2020 than in February 2020 and wider in 2020 than in any other year for three of six vendors (ALEKS, Mathspace, and ST Math).

¹⁴ Initial analyses also examined changes in usage during the five-month period from January 2020 to May 2020. Levels of usage are generally lower in May than in other months, likely because the academic year is winding down and students have already completed standardized testing. Usage in January is generally very similar to usage in February. This was also the case during the 2019-2020 academic year.

Figure 6. Math software usage (in hours per month) by month, year, vendor, and student low-income status when missing values are not replaced with zeroes



Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage.

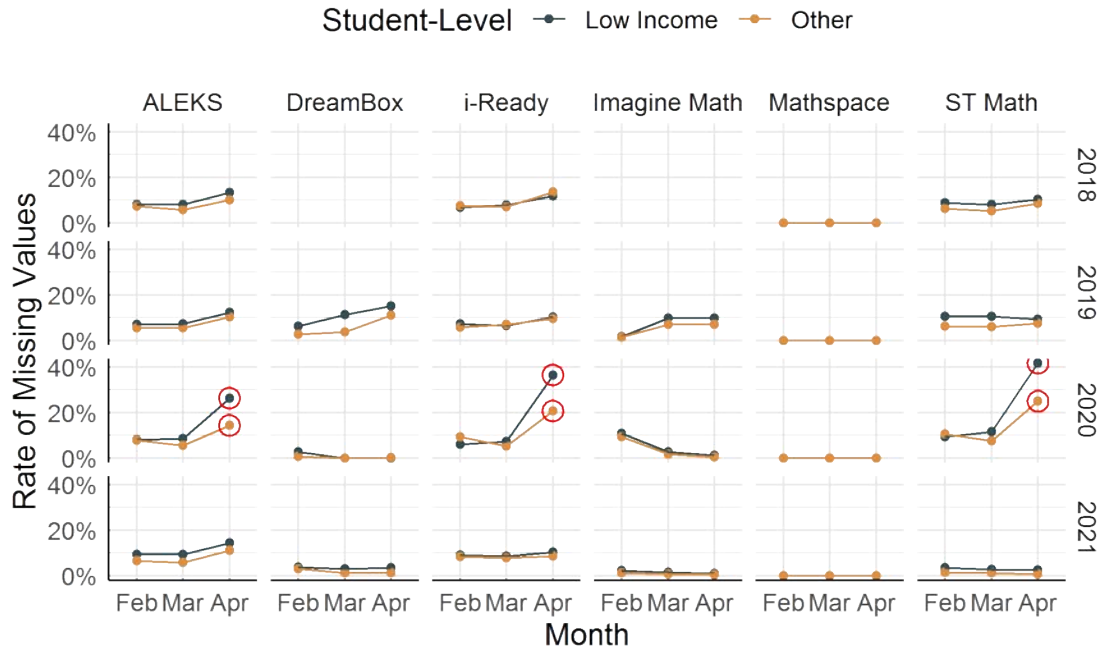
Red ovals highlight substantial gaps in median monthly usage between students who were low-income and other students in 2020 for three of six vendors (ALEKS, Mathspace, and ST MATH). In all three cases, low-income students used the software *less* than other students. The gaps in usage were larger in April 2020 (after the soft closure of Utah’s schools) than in February 2020 (before the soft closure). Gaps were also larger for these vendors in April 2020 than in April of any other year.

These data may, however, underestimate the disparities by low-income status at the student level. Specifically, all summary statistics are based only on those students for whom data was available. As shown in Figure 7, the rate of missing data increased markedly from March 2020 to April 2020 for three vendors – ALEKS, i-Ready, and ST Math – and this increase was much greater among students who were low-income than among other students.¹⁵

Given reports that students who were low-income were less likely than non-low-income students to have access to computers or the Internet during pandemic-related school closures (Ong, 2020), it is plausible that many, if not most, of those missing values represent zero usage. When missing data are replaced with zeroes during this three-month period, disparities by student low-income status become even clearer.

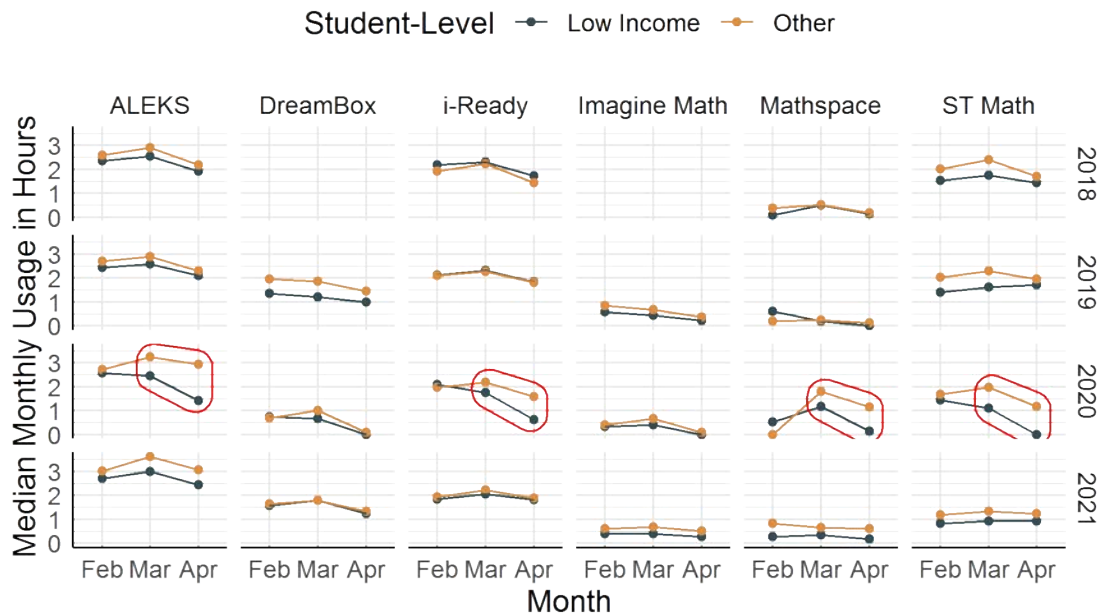
¹⁵ In Figure 7, only orange lines appear for Mathspace. This is because the rate of missing data was 0% for both students who were low-income and other students. As a result, the black and orange lines completely overlap.

Figure 7. Rates of missing data by month, year, vendor, and student low-income status



Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. **Red circles** highlight substantial gaps in rates of missing data in April 2020 between students who were low-income and other students.

Figure 8. Math software usage (in hours per month) by month, year, vendor, and student low-income status when missing values are replaced with zeroes



Missing values replaced with zero

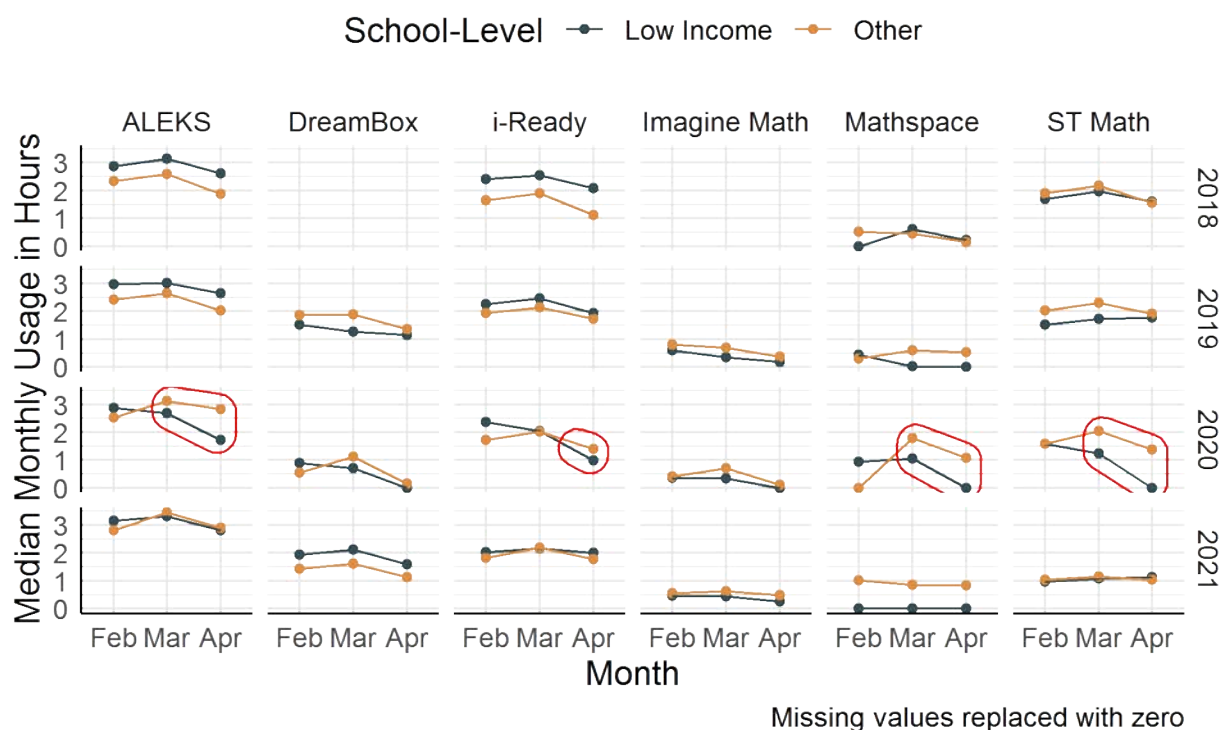
Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. **Red ovals** highlight substantial gaps in median monthly usage between students who were low-income and other students in March 2020 and April 2020.

Specifically, as shown in Figure 8, when missing values are replaced with zeroes, math software usage declines markedly in March and/or April 2020 for students who were low-income for four of six vendors (i.e., ALEKS, i-Ready, Mathspace, and ST Math). These declines either create or widen a gap in usage levels compared with other students.

2c | Were levels of usage from February 2020 to April 2020 related to percent of low-income students at the school?

As shown in Figure 9, the pattern of findings is generally similar when examining the effect of low-income status at the school level on median monthly usage, with students in low-income schools showing steeper declines than students in other schools in math software usage from March 2020 to April 2020 for four of six vendors (i.e., ALEKS, i-Ready, Mathspace, and ST Math).

Figure 9. Math software usage (in hours per month) by month, year, vendor, and school % low-income when missing values are replaced with zeroes



Note. Schools are identified as **low-income** if 40% or more of students were eligible for free or reduced-price lunch. The median monthly usage is preferred over the mean as a measure of central tendency because of positively skewed usage. **Red ovals** highlight substantial gaps in median monthly usage between students who were low-income and other students in March 2020 and April 2020.

2d | Did students who were low-income have lower levels of usage in April 2020 across schools, or did the magnitude of the gap differ by the percentage of low-income students in the school?

Because a significant amount of the variation in software usage in April 2020 occurred across schools (ICCs = .06 to .32), multilevel modeling was used to examine the independent effects of low-income status at the student and school levels on April 2020 usage and to examine whether the gap in usage levels

between students who were identified as low-income and other students differed by the percentage of students who were low-income in the school.

As shown in Table 6, estimates for the effect of low-income status at the student level on software usage in April 2020 (highlighted in orange) show that, across years and vendors, students who were low-income used math personalized software for fewer hours than other students. The gap in mean monthly usage ranged from 0.14 hours (= 8.4 minutes) to 0.60 hours (= 36.0 minutes) less for low-income students. *These estimates controlled for the percentage of students who were low-income at the school level.*

Estimates of the effect of low-income status at the school level on software usage (highlighted in green) were more mixed. For most vendors, there was no relationship. For ST Math, students from low-income schools used the software .60 hours (=36.0 minutes) less than other students. *These estimates controlled for low-income status at the student level.*

Estimates for the interaction between student-level low-income and percent low-income at the school level (highlighted in gray) were not statistically significant, indicating that students who were low-income used the math personalized learning software for less time in April 2020 than students who were not low-income across schools, not just schools with a high (or low) percentage of students who were low-income.

Table 6. Summary of multilevel model predicting April 2020 usage by vendor

Parameters	ALEKS	DreamBox	i-Ready	Imagine Math	Mathspace	ST Math
Regression coefficients (fixed effects)						
Intercept	3.18***	1.33***	1.76***	0.93***	1.41***	1.95***
Student Low-Income	-0.60***	-0.14	-0.35***	-0.19***	-0.19*	-0.52***
School Low-Income	-0.10	-0.43	-0.15	-0.10	0.18	-0.60***
Interaction	-0.07	-0.27	-0.11	-0.09	-0.31	-0.11
Variance components (random effects)						
Residual	15.70	6.62	4.71	2.86	6.40	8.86
Intercept	6.48	0.55	0.99	0.58	3.15	0.71
Slope	0.45	0.00	0.14	0.04	0.06	0.11
Covariance	-0.94	0.02	-0.25	-0.12	-0.39	-0.07

Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. Schools are identified as **low-income** if 40% or more of students were eligible for free or reduced-price lunch. The model includes zero usage for April 2020 if a student had non-zero usage in February 2020 and/or March 2020, but the student did not have usage data for April 2020. That is, a usage value of zero was imputed for April 2020 in these cases.

* $p < .05$. *** $p < .001$.

Research Question Set #3

What was the relationship between math personalized learning software usage and achievement in 2020-2021? Was the relationship between usage and math achievement moderated by low-income status at either the student or school level?

In our final set of analyses, we sought to examine a) whether there was a relationship between math personalized learning software usage and achievement in 2020-2021, and b) whether the relationship between usage and math achievement was moderated by low-income status at either the student or school level. Analyses focused on 2020-2021 given that achievement data were not available for the 2019-2020 academic year because of the Covid-19 pandemic and because usage data were not available for two of the six vendors in 2017-2018 given that these two vendors were not on STEM Action Center's approved vendor list prior to the 2018-2019 academic year. 2020-2021 is also important given that it is the first full academic year following the soft closure of Utah's schools and a year during which many students experienced disrupted learning (e.g., quarantines or hybrid instruction).

We begin this section with a summary of key findings. In the pages that follow, we present detailed findings for Research Question Set #3.

Summary of Findings for Research Question Set #3.

What was the relationship between software usage and student math achievement in 2020-2021, the first full academic year following the soft closure of Utah's schools in March 2020 and a year during which many students experienced disrupted learning?

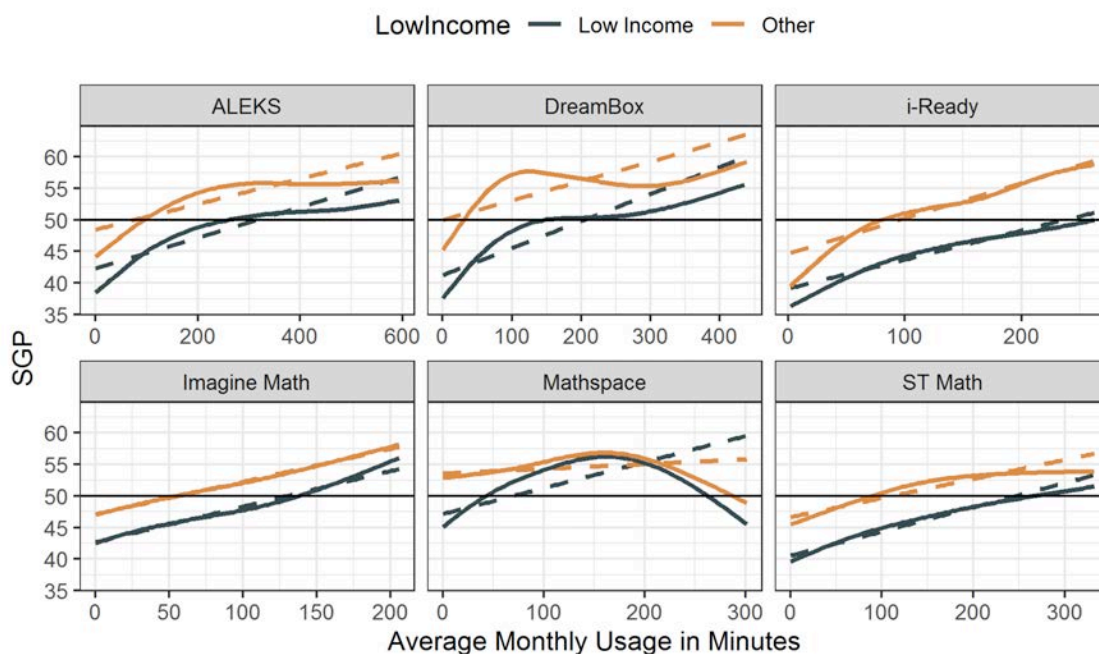
Student use of math personalized learning software was positively related to growth in mathematics for most vendors, with some evidence for diminishing returns at high usage levels for some vendors. For the three vendors for which the relationship was most clearly linear, SGPs increased by between 3.91 and 5.56 points for every hour increase in mean monthly usage. The benefits of math personalized learning software were similar for students attending schools with both lower (i.e., < 40%) and higher (i.e., \geq 40%) percentages of students who were low-income and, generally, for both students who were low-income and other students. When differences emerged, the benefits were stronger for low-income students.

3a | What was the relationship between math personalized learning software usage and achievement in 2020-2021? Was the relationship between usage and math achievement moderated by low-income status at either the student or school level?

RISE student growth percentile (SGP) scores were available for between 70% and 81% of students who had vendor usage data and who were in grades 5 - 10 in the 2020-2021 academic year. Although SGP scores are typically also available for 4th grade students, this was not true in 2020-2021 because these students did not take the RISE assessment in 2019-2020 as a result of the Covid-19 pandemic.

The relationship between math personalized learning software usage and math SGPs in 2020-2021 is represented graphically in Figure 10 for each vendor. The horizontal axis represents mean usage in minutes per month, while the vertical axis represents SGP score. The scale of the horizontal axis varies across vendors because usage levels are much higher for some vendors (e.g., ALEKS) than for others (e.g., i-Ready). Most vendors had a small subset of students with very high usage and an average for those students would be unreliable given their small size. As a result, Figure 10 is based on the bottom 95% of usage levels for each vendor. The solid lines represent a moving average of SGP at each level of usage, with orange lines representing students who are low-income and gray lines representing other students. The dashed lines are best-fitting straight lines to illustrate how well associations between usage and achievement are described by a linear relationship.

Figure 10. Relationship between math software usage (in minutes per month) and student growth percentiles in the 2020-2021 academic year by vendor



Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch.

Three vendors – i-Ready, Imagine Math, and ST Math – show moving averages that are well-represented with a best-fitting straight line, as indicated by the close alignment of the solid lines to the dashed lines. The patterns for ALEKS and DreamBox are somewhat different. Here, software usage shows diminishing returns above 200 minutes. The pattern for Mathspace stands out. Here, there is a *negative* relationship between usage and achievement when usage exceeds 200 minutes. The curvilinear relationship between

usage and SGPs for Mathspace deviates so drastically from linear that it would be inappropriate to use a linear model. As a result, Mathspace is excluded from the list of vendors in multilevel modeling.

3b | Was the relationship between usage and math achievement moderated by low-income status at either the student or school level?

Because a significant amount of the variation in software usage occurred across schools (ICCs = .14 to .17), multilevel modeling was used to examine whether math personalized learning software usage during the 2020-2021 academic year predicted scores on math achievement tests administered in Spring 2021 and whether the relationship between usage and achievement was moderated by either student or school-level low-income status.

As shown in Table 7, estimates for the effect of math software usage on SGPs (highlighted in orange) indicated that, across vendors, math personalized software usage was positively associated with SGPs. Specifically, results showed that, on average, SGPs increased by between 1.99 and 5.56 points for every hour increase in mean monthly usage. For the three vendors for which the relationship was most clearly linear, SGPs increased by between 3.91 and 5.56 points for every hour increase in mean monthly usage. These estimates controlled for low-income status at both the student and school level.

Estimates of the effects of low-income status at both the student and school level on SGPs (highlighted in green) indicated that, across vendors, low-income status predicted lower SGP scores. Specifically, results indicated that, on average, low-income students had SGP scores that were between 3.55 and 4.98 points lower than other students. Likewise, students who attended low-income schools had SGP scores that were between 5.54 and 10.34 points lower than other students. These estimates controlled for software usage.

Estimates for the interaction between software usage and low-income status at either the student or school level (highlighted in gray) were generally not statistically significant, indicating that students who were low-income or who attended schools in which a higher percentage of students were low-income benefited from software usage to the same degree as other students. The one exception to this finding was for low-income students using ALEKS. Here, the results indicated a stronger, positive relationship between software usage and SGPs among low-income students compared to other students.

Table 7. Summary of multilevel model predicting 2021 RISE Student Growth Percentile (SGP) scores from math software usage by vendor

Parameters	ALEKS	DreamBox	i-Ready	Imagine Math	ST Math
Regression coefficients (fixed effects)					
Intercept	51.51***	48.82***	49.45***	51.51***	46.54***
Period Usage (in hours)	1.99***	3.00***	5.12***	5.56***	3.91***
Student Low-Income	-3.55***	-3.56***	-3.95***	-4.41***	-4.98***
School Low-Income	-6.02***	-6.87***	-8.25***	-5.54	-10.34***
Interaction: Usage by Student LI	0.29*	0.84	0.66	-0.92	-0.03
Interaction: Usage by School LI	0.60	0.08	-0.85	1.25	-0.90
Variance components (random effects)					
Residual	702.88	677.07	683.37	685.91	666.74
Intercept	126.94	123.13	129.11	133.22	125.78
Slope	3.70	11.14	13.59	10.02	8.26
Covariance	-1.41	6.56	-0.21	1.21	9.94

Note. Students are identified as **low-income** if they were eligible for free or reduced-price lunch. Schools are identified as low-income if 40% or more of students were eligible for free or reduced-price lunch. *** $p < .001$.

Implications

Results from the current study indicate that students who were low-income used math personalized learning software for less time than other students from 2017-2018 to 2020-2021 and that the gap in usage by student low-income status widened immediately after the soft closure of schools in Utah in March 2020. Importantly, the gaps in usage by student low-income status are modest – between 6 and 34 minutes per month – and likely smaller than they might have been without ongoing, statewide efforts to close the digital divide (e.g., Utah Education and Telehealth Network, 2020; Utah State Board of Education, 2020).

Attention to even small gaps in usage by student low-income status is warranted given evidence that many students benefit from using math personalized learning software regardless of their eligibility for free or reduced-priced lunch. In the current study, the effect of math personalized learning software use on mathematics achievement was generally positive, with student growth percentile (SGP) scores increasing by between 1.99 and 5.56 points, on average, for every hour increase in mean monthly usage. For the three vendors for which the relationship was most clearly linear, SGPs increased by between 3.91 and 5.56 points for every hour increase in mean monthly usage. These findings suggest that increasing math personalized learning software use has the potential to reduce a substantial gap in SGP scores between low-income and other students (here, between 3.55 and 4.98 points).

Importantly, recommendations to work to increase opportunities for students who are low-income to use math personalized learning software should be approached with care. First, this is a correlational study. It is possible that a third variable (e.g., classroom instructional practices that are correlated with high levels of software use), not software use itself, is the true cause of achievement gains. Importantly, however, the finding that usage is positively related to achievement gains is consistent with prior research conducted by the UEPC and others, including studies employing rigorous experimental and quasi-experimental designs mathematics (see Cheung & Slavin, 2013, Hillmayr, Ziemwald, Reinhold, Hofer, & Reiss, 2020, and Young, Gorumek, & Hamilton, 2018, for meta-analytic reviews). Second, for several vendors, the benefits of software usage began to dwindle when usage exceeded 200 minutes (or 3.33 hours) per month and, for one vendor, usage beyond this level appeared to have deleterious effects. Future work will be important in understanding the conditions under which software use has its greatest impact, including by addressing the following questions:

1. What specific implementation practices for math personalized learning software are most closely associated with achievement gains? Are economically marginalized students more likely to benefit from some implementation practices than others?
2. What challenges do students face in utilizing math personalized learning software? Do these challenges vary by low-income status at either the student or school level?
3. What challenges do teachers face in aligning math personalized learning software use to other types of mathematics instruction to create effective blended learning environments? Are these challenges heightened in schools in which a high number of students are from economically marginalized backgrounds?
4. How can math personalized learning software be used in combination with other interventions (e.g., high-dosage tutoring)? Which combinations of interventions are most impactful, and for which students?
5. Do teachers and students have the supports they need to use math personalized learning software effectively? To what degree does access to high-quality professional learning opportunities or access to one-to-one support for students (e.g., via tutoring) vary by school-level low-income status?

6. To what degree do teachers use engagement and diagnostic data from math personalized learning software to inform their regular classroom instruction or students' software use? Does use of these data vary by school-level low-income status?

The current study also illuminates the need for additional research on how other student-level characteristics (e.g., student race/ethnicity or student grade level) or school-level characteristics (e.g., % of English language learners) impact both math personalized learning software use and the relationship between software use and achievement. Additionally, future work will be important in understanding how software is being used during out-of-school time hours and in determining the degree to which student scores on diagnostic assessments administered via math personalized learning software are correlated with scores on state assessments (e.g., RISE assessments). Answers to the latter question will be important in informing conversations with both vendors and educators about the degree to which software-based assessment data can be useful in identifying (and intervening) with students who are at risk for poor performance on state assessments.

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