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Associations Between IXL Personalized Learning Software Use and Student Mathematics Achievement in Utah: 2020-2021

THE UNIVERSITY OF UTAH
UTAH EDUCATION POLICY CENTER

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THE UNIVERSITY OF UTAH
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Bridging Research, Policy, and Practice

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Introduction

Background

Mathematics performance among students in the United States lags behind that of students in many other countries. For example, the mean mathematics score of 15-year-old students in the United States on the Program for International Student Assessment (PISA) is lower than the mean score of students in most comparable developed nations, including the Netherlands, Switzerland, Canada, Belgium, Denmark, the United Kingdom, and Germany (OECD, 2021). Although mathematics performance among U.S. students has shown improvements in recent decades, the Covid-19 pandemic has resulted in steep declines since 2019. Results from the NAEP Mathematics Assessment indicate that the average fourth-grade mathematics score decreased from 2019 (pre-pandemic) to 2022 (post-pandemic) and was lower than all previous assessments going back to 2005. The average eighth-grade mathematics score decreased from 2019 to 2022 and was lower than all previous assessments going back to 2003.[1]

One strategy that might be employed to address historical underperformance in mathematics and more recent learning loss associated with the Covid-19 pandemic is to increase the utilization of technology to supplement mathematics instruction. Supporting this approach, several recent meta-analyses and other systematic reviews have linked the use of educational technology – including math personalized learning software – to positive achievement outcomes in mathematics for K-12 students (Broderson & Melluso, 2017; Cheung & Slavin, 2013; Li & Ma, 2010; Ma, Adesope, Nesbit, & Liu, 2014; but see Dynarski et al., 2007). Importantly, the effect of educational technology interventions on student achievement outcomes appears to be moderated by a variety of factors including the type of educational technology used (Ran, Kasli, & Secada, 2021) and the duration and intensity of use (Campuzano, Dynarski, Agodini, & Rall, 2009; Cheung & Slavin, 2013). Prior research in Utah indicates, for example, that math personalized learning software is most likely to predict strong mathematics achievement among students with relatively high levels of usage (Su, Rorrer, Owens, Pecsok, Moore, & Ni, 2020).

Current Study

The purpose of the current study was to examine associations between IXL personalized learning software use and student math achievement outcomes. Two research questions were addressed:

1. What is the relationship between the amount of weekly IXL program use and student math proficiency as measured by statewide math assessments, controlling for student demographic and educational characteristics?

2. What is the relationship between the amount of weekly IXL program use and student math performance as measured by theta scores from statewide math assessments, controlling for student demographic and educational characteristics?

The methods used in the current study model those used in previous evaluation 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.[2] 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.

[1] https://www.nationsreportcard.gov/highlights/mathematics/2022/

[2] https://stem.utah.gov/educators/opportunities/k-12-math-personalized-learning-software-grant/

Data Sources

The data used for this study came from two sources. First, using a secure platform, IXL provided student software usage data to the UEPC for five schools in the state of Utah for the 2020-2021 academic year. Second, the Utah State Board of Education provided student demographic and achievement data to the UEPC via a Data Sharing Agreement.[3]

Student achievement data included 2020 mathematics proficiency scores and theta scores from a statewide math assessment (i.e., the Readiness Improvement Success Empowerment, or RISE, assessment which is administered to 3rd to 8th grade students). A dataset was created by joining student software usage data provided by IXL to USBE demographic, educational, and achievement data using a matching algorithm using student name, grade, and school. Records were excluded from the dataset based on the following criteria: 1) a student was in kindergarten through second grade, 2) IXL student usage data could not be matched to USBE data, 3) IXL student usage data indicated excessively high average weekly use, or 4) IXL student usage data indicated less than one minute of reported program use or zero logins during the school year.

Data Analysis

The purpose of the current study was to examine associations between IXL personalized learning software use and student math achievement outcomes. *For the purposes of these analyses, IXL users were defined as students who logged into IXL for at least one minute during the school year and were enrolled in one of the five schools in Utah for which data were provided by IXL. IXL non-users were defined as students from comparison schools in Utah who did not use IXL.* Comparison schools were identified using propensity score matching as shown in Figure 1 (Step 1) and described in detail below. Methods for establishing levels of usage and for conducting linear and logistic regression analyses are shown in Figure 1 (Steps 2-4) and described in detail below.

Step 1. Propensity Score Matching

Comparison schools were identified through propensity score matching. Propensity score matching is a technique used to minimize the chances that differences in achievement outcomes between IXL users and IXL non-users are the result of factors other than IXL use, including school-level demographic characteristics.

All matches were made based on school-level metrics of school type (e.g., elementary vs. middle school), race/ethnicity (e.g., % of students who identified as African American or Black), gender (i.e., % of students who identified as female), school location (e.g., city vs. rural), chronic absence (i.e., % of students identified as being chronically absent), special education status (% of students identified as receiving special education), English learner status (% of students identified as English learners), low income status (% of students qualifying for Free or Reduced Price Lunch), and mobility (% of students attending more than one school in a given academic year).

[3] 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 and do not necessarily reflect the views or positions of the USBE or the University of Utah.

Figure 1. Overview of data analysis procedures

1. **PROPENSITY SCORE MATCHING.** To reduce selection biases, propensity score matching was used to identify schools that were similar to the IXL-using schools included in the current study. All matches were made based on school-level metrics of school type, race/ethnicity, gender, school location, chronic absence status, special education status, English learner status, low income status, and mobility.

2. **USAGE QUARTILES.** IXL users were divided into four usage quartiles based on their average minutes of weekly IXL use each academic year.

3. **L0GISTIC REGRESSION.** Logistic regression was used to estimate the relationship between weekly IXL use and math proficiency as measured by RISE assessments. Models included student-level indicators of grade level, race/ethnicity, gender, school location, chronic absence status, special education status, English learner status, low income status, and mobility.

4. **LINEAR REGRESSION.** Linear regression was used to estimate the relationship between weekly IXL use and RISE assesssment theta scores. Models included student-level indicators of grade level, race/ethnicity, gender, school location, chronic absence status, special education status, English learner status, low income status, and mobility.

Only schools that were *not* supported by a STEM Action Center license in 2020-2021 were considered as potential comparison schools. In limiting potential comparison schools in this way, we sought to minimize the possibility that IXL users were being compared to IXL non-users who were users of math personalized learning software from another vendor that has already met the criteria for being designated as an approved vendor in Utah through the STEM Action Center based on an evaluation that is similar to the one presented here. This approach does not exclude the possibility that students from comparison schools were users of math personalized learning software from a vendor that is not approved through the STEM Action Center or that students from comparison schools were using a license for math personalized learning software from a STEM Action Center-approved vendor that was provided by an entity other than the STEM Action Center.

Step 2. Usage Quartiles

Students were divided into four usage quartiles based on their average minutes of weekly IXL use across the academic year.

Step 3. Logistic Regression

Logistic regression was used to estimate the relationship between weekly IXL use and math proficiency as measured by test scores on statewide math assessments. Math proficiency is a binary variable (proficient or not proficient) that indicates whether a student appears to be on track for college and career readiness based on end-of-year, statewide summative math test scores. Models included student-level indicators of grade level, race/ethnicity, gender, school location, chronic absence status, special education status, English learner status, low-income status, and mobility as covariates to estimate the impact of IXL use more precisely. In all logistic regression models, the math proficiency of IXL users at each usage quartile is compared to the math proficiency of IXL non-users from comparison schools, controlling for student demographic and educational characteristics. That is, the tests of interest compared the proficiency of all non-users to the proficiency of users in each of the quartiles: non-users vs. first quartile, non-users vs. second quartile, etc. This approach permits a covariate-adjusted comparison of users to non-users that also respects the possible moderating influence of amount of usage. We were unable to control for prior year proficiency in logistic regression analyses as statewide math assessments were not administered in 2019-2020 due to the Covid-19 pandemic.

Step 4. Linear Regression

Linear regression was used to estimate the relationship between weekly IXL use and math performance as measured by theta scores on statewide math assessment. Theta scores represent student performance relative to other students and are similar to z-scores with a mean close to zero and a standard deviation close to one. Models included student-level indicators of grade level, race/ethnicity, gender, school location, chronic absence status, special education status, English learner status, low-income status, and mobility as covariates to estimate the impact of IXL use more precisely. For all linear regression models, theta scores of IXL users at each quartile are compared to theta scores of IXL non-users from comparison schools, controlling for student demographic and educational characteristics. We were unable to control for prior year proficiency in logistic regression analyses as statewide math assessment tests were not administered in 2019-2020 due to the Covid-19 pandemic.

Findings

The demographic and educational characteristics of IXL users and IXL non-users from comparison schools are presented in Table 1. As shown, the two groups were similar on most matching variables after propensity score matching and filtering (e.g., to remove students without achievement data). The largest differences between the two groups emerged for school location.

Table 1. Demographic and educational characteristics of matched IXL users and IXL non-users in 2020-2021

	Users (n = 1020)	Non-Users (n = 882)
Grade level		
3rd grade	28.4%	28.0%
4th grade	21.4%	21.7%
5th grade	32.6%	32.0%
6th grade	17.5%	9.4%
7th grade	0.0%	9.0%
Race/Ethnicity		
African American/Black	0.4%	0.5%
Am. Indian/Alaskan Native	0.3%	0.3%
Asian	0.3%	1.0%
Latino/Hispanic	9.0%	12.1%
Native Hawaiian/Pacific Islander	0.7%	0.5%
Multiple Races	3.0%	1.6%
White	86.3%	84.0%
Other Student Characteristics		
Female	51.4%	49.3%
City	0.5%	0.7%
Rural	22.2%	45.0%
Suburb	35.8%	32.9%
Town	41.6%	21.4%

Chronic Absence	21.7%	17.9%
Special Education	13.8%	16.6%
English Learner	5.4%	9.4%
Low Income	32.3%	35.3%
Mobile	4.9%	10.0%

IXL users were divided into four usage quartiles based on their average minutes of weekly IXL use each academic year. Cutoffs for usage quartiles for 2020-2021 are presented in Table 2.

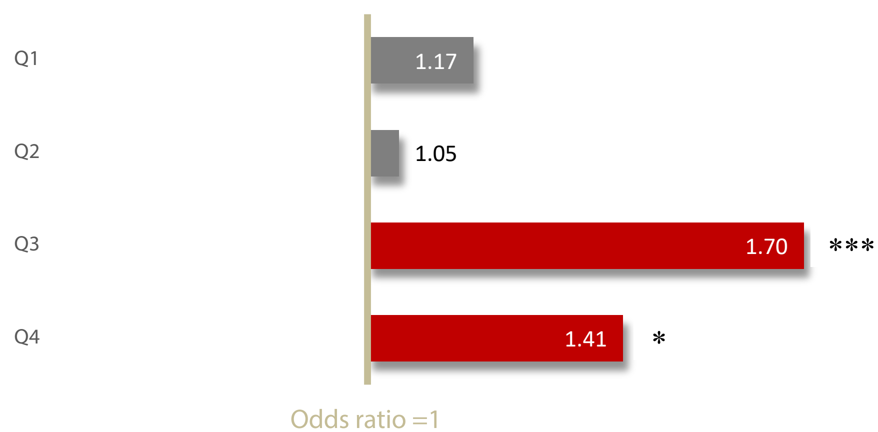
Table 2. Cutoffs for weekly IXL usage quartiles in 2020-2021

Quartile	Number of minutes
Q1	less than 11 minutes
Q2	11 to 20 minutes
Q3	20 to 35 minutes
Q4	more than 35 minutes

Associations between weekly IXL usage quartiles and student math proficiency

Logistic regression was used to compare the math Proficiency of IXL users in each usage quartile to the math proficiency of IXL non-users from comparison schools, controlling for student demographic and educational characteristics. As shown in Figure 2, **IXL users in both the third and fourth usage quartiles (i.e., students with 20 minutes or more of weekly IXL use) were more likely to be proficient in math than IXL non-users from comparison schools, *ps* < .05.** IXL users in the first and second usage quartiles were, in contrast, neither more nor less likely to be proficient in math than IXL non-users from comparison schools. Odds ratios are presented in Figure 2. The full set of model results are presented in Table 3 in the Appendix.

Figure 2. Odds of math proficiency for IXL users compared to non-users by usage quartile in 2020-2021



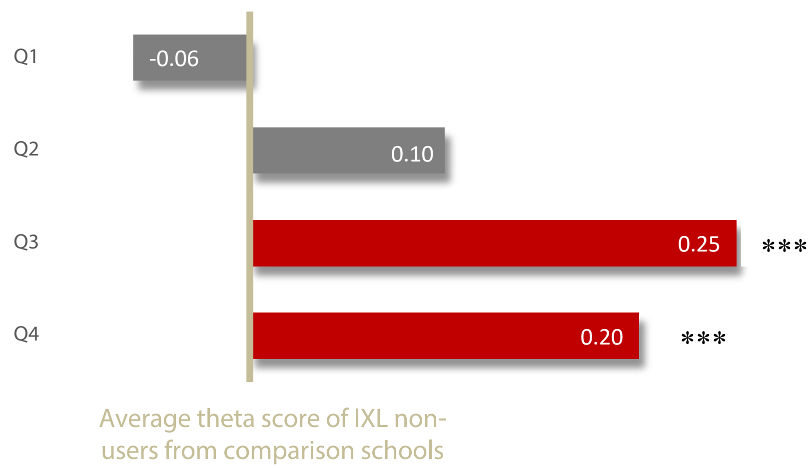
** p < .05. *** p < .001.*

Note. The tan vertical bar represents an odds ratio of 1. When the odds ratio is equal to 1, the odds of achieving math proficiency are equal for IXL users and IXL non-users from comparison schools, controlling for student demographic and educational characteristics. When the odds ratio is greater than 1, it indicates that math proficiency is *more* likely among IXL users than IXL non-users from comparison schools. The odds ratios for Quartiles 3 and Quartile 4 indicate that, in 2020-2021, the odds of math proficiency for IXL users in these quartiles are 1.70 times higher and 1.41 times higher, respectively, than the odds of math proficiency for IXL non-users from comparison schools, controlling for student demographic and educational characteristics. These differences are statistically significant as indicated by the **red** bars.

Associations between weekly IXL usage quartiles and student theta scores

Linear regression was used compare the theta scores of IXL users in each usage quartile to the theta scores of IXL non-users from comparison schools, controlling for student demographic and educational characteristics. As shown in Figure 3*,* **IXL users in both the third and fourth usage quartiles (i.e., students with 20 minutes or more of weekly IXL use) had higher theta scores in math than IXL non-users from comparison schools, *ps* < .001.** IXL users in the first and second usage quartiles, in contrast, had theta scores that were not significantly different than the theta scores of IXL non-users from comparison schools. Regression coefficients are presented in Figure 3. The full set of model results are presented in Table 4 in the Appendix.

Figure 3. Theta scores for IXL users compared to non-users by usage quartile in 2020-2021



*** $p < .001$.

Note. The tan vertical bar represents the average theta score of IXL non-users from comparison schools. IXL users are compared to this baseline. **Red** bars indicate that, in 2020-2021, IXL users in the third quartile and fourth quartile had theta scores that were significantly higher (by .25 and .20 points, respectively) than the theta scores of non-users, controlling for student educational and demographic characteristics.

Considerations

The results of the current study suggest that Utah students who, on average, use IXL for 20 minutes or more per week perform better on statewide math assessments than students who do not use IXL. This finding is consistent with IXL's implementation fidelity and usage recommendations which indicate that, for "optimal usage," students should reach proficiency in at least two skills per week (where proficiency in one skill takes 15 – 20 minutes to achieve) (An, Schonberg, & Bashkov, 2022).

Given evidence that the benefits of personalized math software use may be enhanced when teachers are trained to effectively integrate technology into classroom instruction (Foulger, Graziano, Schmidt-Crawford, & Slykhuis, 2017), future research and evaluation efforts might focus on whether and how teacher behaviors moderate the impact of IXL use on student outcomes. For example, IXL indicates that one effective implementation approach is to assign IXL activities to students following regular classroom instruction to allow students to practice key concepts. Teachers are encouraged to guide this work by checking for student understanding using IXL Analytics (https://www.ixl.com/resources/implementation-strategies). It is unclear from the current study how often teachers in Utah use IXL to support core math curricula or how frequently they use IXL Analytics to guide this work. Likewise, it is unclear whether teachers who routinely use IXL Analytics have students who are more likely to benefit from IXL use. Given evidence that the benefits of personalized math software use may also be impacted by student behaviors, future research and evaluation efforts might also focus on the degree to which student outcomes are moderated by specific student behaviors beyond average weekly use. Student behaviors of interest might include the number of activities completed per day or per week, idle-to-active time per session, and the percentage of sessions that occur during vs. outside the regular school day (Heinrich, Darling-Aduana, Good, & Cheng, 2019). Future work will also be important in determining how teacher knowledge and behaviors, student behaviors, and teacher and student characteristics (e.g., # of years of teaching or race/ethnicity) might interact to impact student outcomes. This work will be critical in helping vendors and educators identify and accommodate the unique needs of all students.

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Appendix

Table 3. Logistic regression predicting math proficiency from IXL usage quartiles (2020-2021)

Predictor Variable	Estimate	Std Error	*z*	*p*	Odds Ratio	95% CI for OR (low, high)	
Intercept	0.74	0.14	5.12	.000***	2.09	1.58	2.78
Use Quartile							
Quartile 1	0.15	0.19	0.81	.419	1.17	0.80	1.70
Quartile 2	0.05	0.16	0.34	.732	1.05	0.78	1.43
Quartile 3	0.53	0.16	3.29	.001***	1.70	1.24	2.33
Quartile 4	0.34	0.17	1.98	.048*	1.41	1.00	1.97
Grade Level							
3rd grade	0.46	0.14	3.35	.001***	1.59	1.21	2.09
4th grade	0.05	0.15	0.31	.760	1.05	0.78	1.41
6th grade	-0.15	0.17	-0.87	.383	0.86	0.62	1.21
7th grade	0.46	0.29	1.60	.109	1.59	0.90	2.80
Race/Ethnicity							
African American/Black	-2.28	1.10	-2.07	.039*	0.10	0.01	0.63
American Indian/Alaskan Native	0.18	0.88	0.20	.842	1.19	0.20	7.46
Asian	-0.16	0.70	-0.24	.814	0.85	0.20	3.25
Latino/Hispanic	-0.42	0.25	-1.65	.100	0.66	0.40	1.08
Native Hawaiian/Pacific Islander	-0.21	0.68	-0.30	.761	0.81	0.19	3.04
Multiple Races	-0.17	0.34	-0.52	.606	0.84	0.43	1.63
Other Student Characteristics							
Female	-0.35	0.10	-3.40	.001***	0.70	0.57	0.86
City	-1.43	1.13	-1.26	.206	0.24	0.01	1.64
Rural	-0.19	0.14	-1.39	.165	0.82	0.63	1.08
Town	0.23	0.15	1.61	.108	1.26	0.95	1.68
Chronic Absence	-0.69	0.13	-5.24	.000***	0.50	0.39	0.65
Special Education	-1.71	0.17	-10.28	.000***	0.18	0.13	0.25
English Learner	-0.73	0.32	-2.30	.021*	0.48	0.26	0.89
Low Income	-0.71	0.12	-5.74	.000***	0.49	0.39	0.63
Mobile	-0.84	0.23	-3.59	.000***	0.43	0.27	0.68

Note. Each estimated coefficient is the expected increase or decrease in the log odds of math proficiency for the associated predictor variable holding the other predictor variables constant. Odds ratios are calculated by exponentiating these estimates.

Source: USBE Records and IXL Data

Table 4. Linear regression predicting math theta scores from IXL usage quartiles (2020-2021)

Predictor Variable	Estimate	Std Error	*t*	*p*	95% CI for Est (low, high)	
Intercept	-0.78	0.05	-16.10	.000***	-0.88	-0.69
Use Quartile						
Quartile 1	-0.06	0.06	-0.96	.337	-0.18	0.06
Quartile 2	0.10	0.05	1.83	.067	-0.01	0.20
Quartile 3	0.25	0.05	4.76	.000***	0.15	0.36
Quartile 4	0.20	0.06	3.50	.001***	0.09	0.32
Grade Level						
3rd grade	-1.10	0.05	-24.11	.000	-1.19	-1.01
4th grade	-0.57	0.05	-11.27	.000	-0.67	-0.47
6th grade	0.78	0.06	13.54	.000	0.67	0.90
7th grade	1.55	0.10	15.85	.000	1.36	1.74
Race/Ethnicity						
African American/Black	-0.69	0.26	-2.63	.009**	-1.21	-0.18
American Indian/Alaskan Native	0.31	0.30	1.02	.309	-0.29	0.90
Asian	-0.04	0.22	-0.17	.869	-0.47	0.40
Latino/Hispanic	-0.17	0.08	-1.98	.048*	-0.33	0.00
Native Hawaiian/Pacific Islander	-0.05	0.24	-0.22	.830	-0.51	0.41
Multiple Races	-0.15	0.12	-1.28	.199	-0.38	0.08
Other Student Characteristics						
Female	-0.18	0.03	-5.08	.000***	-0.25	-0.11
City	-0.66	0.31	-2.13	.034*	-1.27	-0.05
Rural	-0.07	0.05	-1.59	.112	-0.17	0.02
Town	0.09	0.05	1.94	.053	0.00	0.19
Chronic Absence	-0.29	0.04	-6.65	.000***	-0.38	-0.21
Special Education	-0.79	0.05	-16.02	.000***	-0.89	-0.70
English Learner	-0.28	0.10	-2.76	.006**	-0.48	-0.08
Low Income	-0.28	0.04	-6.84	.000***	-0.37	-0.20
Mobile	-0.29	0.08	-3.84	.000***	-0.44	-0.14

Note. Each estimated coefficient is the expected difference in theta scores between the predictor variable and the reference group holding the other predictor variables constant.

Source: USBE Records and IXL Data