Edulastic

Impact of Edulastic on Math and Reading Growth

Research support for ESSA Tier 3

Executive Summary

Drawing from publicly available data on Ohio's 4th to 8th-grade students, this correlational study investigates the impact of an online assessment tool, Edulastic, on academic growth. The results strongly suggest that Edulastic is beneficial for student learning, with somewhat stronger evidence for its efficacy as a math intervention. The study's design and findings meet the criteria for ESSA Tier 3–promising evidence.

Introduction

Assessments are an integral part of the education system and serve many purposes. Summative assessments can capture a snapshot of student learning and are often used for school or district accountability purposes. Formative assessments can be used both to help students learn and as a diagnostic tool to help teachers identify learning gaps (Shute & Kim, 2013). Digital assessments have the potential benefit of providing real-time feedback, which allows teachers to make informed modifications to their curriculum (Neumann et al., 2019).

This study seeks to investigate the impact of Edulastic, an online assessment tool, in the state of Ohio during the 2015-16 to 2018-19 school years.

Using publicly available archival data for math and reading state assessments in grades 4-8, this study controls for selection bias by including some school-level demographic information in multilevel models. The study's design and findings meet the criteria for Every Student Succeeds Act (ESSA) Tier 3–promising evidence.

Intervention

Edulastic is a K-12 digital assessment platform that offers educators a suite of tools to administer online formative and summative assessments across grades and subjects.

The user-friendly platform enables standards mastery tracking and features over 50 technology-enhanced item types, options for customization, and standards-aligned content. Teachers can track student progress in real time to identify students who need more support and adjust instructional decisions accordingly. District or school administrators can deliver benchmark exams and access site-wide insight reports to understand where additional resources may be needed in the classroom.

Study Design

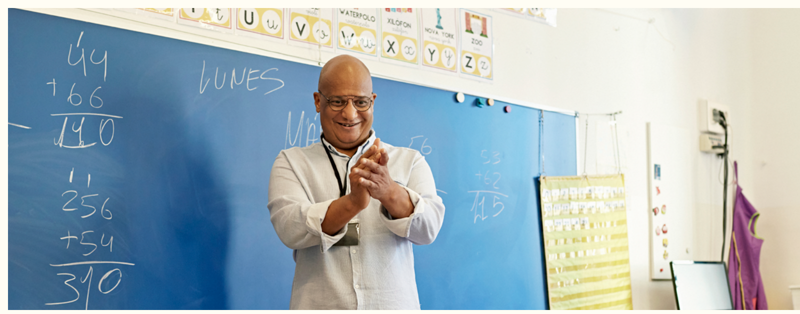
Measure of Academic Growth

The outcome measures in this study are annual math and reading value-added scores on Ohio's state tests (OSTs). We draw from publicly available data on OST value-added scores at the grade-by-school level among Ohio's 4th to 8th-grade students. The value-added measures describe *the extent to which student gains on test scores in a given year for a given grade level of students were different from the expected (or state-averaged) gains in that year.*

The Department of Education constructs the scores in an attempt to measure student academic growth as compared to other schools. In Ohio, the value-added metric does not account for demographic variables; however, it uses each student's full test history as a control for predicted performance (SAS, 2023). Reading and math are the only two tests given consecutively across these grades, thus allowing the calculation of value-added measures.

We, therefore, focus the analysis on math and reading value-added scores. We also limit the analysis between the 2015-16 to 2018-19 school years because the state changed its testing and value-added reporting regime in 2016 and because of the impact of the COVID pandemic beginning in the 2019-20 school year.

The Ohio Department of Education releases value-added measures in a normal curve equivalent (NCE) metric, which transforms scaled scores into a normal distribution of growth. To be consistent with the typical effect size reporting in the educational evaluation literature, we transform the NCE scores to z-scores, i.e. standard deviations of growth in a normal distribution. The z-scored value-added scores are then used as the dependent variable in the models described below. The model estimates can therefore be interpreted as standard deviation changes in average test scores.



Sample Construction

This study is conducted at the grade level within schools, i.e., *the central unit of analysis is the group of students enrolled in a given grade in a given school in a given year.* Reading and math scores are reported separately and willbe analyzed separately. For example, the 5th grade at Springville Elementary could have 8 data points–one for each academic subject, each year of the study. We use data from the full population of Ohio public schools serving students in grades 4-8, with the exclusion of schools that opened or closed entirely during the period of study.

Approximately 6 percent of the remaining grade-by-school combinations have a missing value-added score in some year. These missing values are due to privacy censoring on value-added scores with less than 10 students enrolled. We retain these schools in the sample but drop missing years. *The final analytic sample consists of 2,423 unique schools yielding 22,426 grade-by-school-by-year observations for math and 22,498 for reading.*

Edulastic Usage

To measure effect sizes of Edulastic usage, we employ a binary indicator to determine whether there is a record of a teacher in a given grade at a given school administering an Edulastic assessment in reading or math in a given school year. Within each academic subject, if there is a record of Edulastic usage in a grade-by-school-by-year combination, it is coded as one. If there is no usage, it is coded as zero.

This coarse measurement of Edulastic usage is necessary to align with the publicly available assessment data, which is only available at the grade-by-school level for each subject. We only include usage during school months prior to that year's Ohio state standardized assessment administration: August through April. **Table 1** displays the frequency of Edulastic usage by grade band and subject.

Table 1: *Number of grade-by-school-by-year combinations of Edulastic usage by subject*

Math			
	Elementary (4th-5th Grades)	Middle (6th-8th Grades)	Row Totals
Number of grade-by-school-by-year combinations that **did not** use Edulastic	10,222	9,593	19,815
Number of grade-by-school-by-year combinations that **used** Edulastic	1,192	1,419	2,611
Total	11,414	11,012	22,426
Reading			
	Elementary (4th-5th Grades)	Middle (6th-8th Grades)	Row Totals
Number of grade-by-school-by-year combinations that **did not** use Edulastic	10,400	10,184	20,548
Number of grade-by-school-by-year combinations that **used** Edulastic	1,021	893	1,914
Total	11,421	11,077	22,498

Note: *Data drawn from Edulastic administrative sources and the Ohio Department of Education's public resources. Each observation is a grade-by-school-by-year combination.*

Analytic Methods

To estimate the effects of Edulastic usage in any given grade-by-school-by-year combination, separate linear multilevel models (MLMs) for reading and math were run using the z-scored value-added score as the dependent variable. Value-added scores were converted to z-scores to facilitate interpretation and can be interpreted as an effect size.

To control for selection bias in each model, we include several covariates that were available from public data: the percentage of students eligible for free or reduced-price lunch (a proxy for poverty), the percentage of students classified as disabled, and the percentage of students who identify as Black, Hispanic, Asian/Pacific Islander, American Indian or Alaska Native, and multiracial.[1] Additionally, we include grade band as a binary predictor, where 4th and 5th grades are elementary and 6th-8th grades are middle. To account for the fact that grades are nested within schools, we include school as a random intercept. Models were constructed using the lme4 package in R (Bates et al., 2015).

Findings

The main predictor of interest, or independent variable, is the use of Edulastic assessments in each grade-by-school-by-year combination (Edulastic non-users = 0; Edulastic users = 1). In the model output (see appendix for model outputs), a positive, statistically-significant, estimate for Edulastic assessments would indicate a positive effect of Edulastic usage on academic growth while controlling for selection bias with the included covariates.

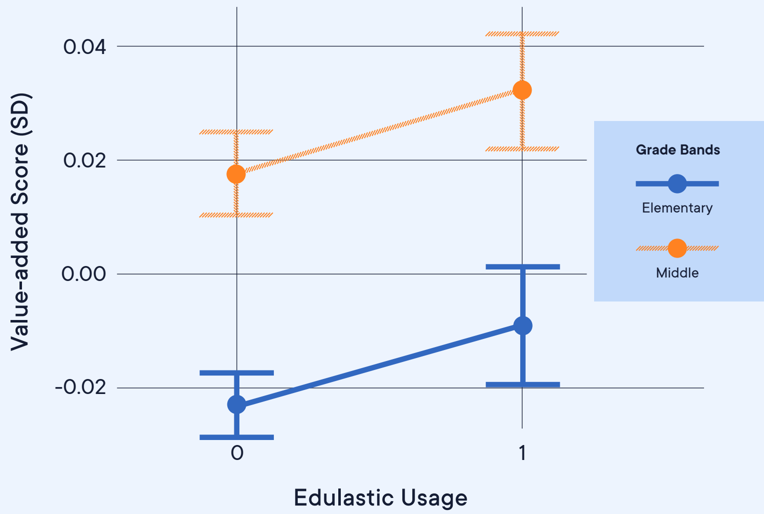
To achieve more parsimonious models, several covariates, specifically the percentage of Asian/Pacific Islander, Hispanic, and multiracial, were not retained in the final models. ***We found that Edulastic usage has a small but positive effect on both math and reading growth in grades 4-8.*** As noted in Kraft (2020), smaller effect sizes could be expected in studies with large n-sizes, which is the case in this study.

Math Findings

For the math model, (see Table 2 in the appendix for full model results) the simple ***effect of assessments is significant, indicating that the use of Edulastic has a positive impact on math growth in grades 4-8*** ($b = 0.014$, $SE = 0.005$, $p < 0.01$). The model estimate for assessments ($b = 0.014$) can be interpreted as an effect size.

The significant effect of grade band ($b = 0.042$, $SE = 0.004$, $p < 0.001$) indicates that middle school students had a higher average value-added score compared to elementary students while controlling for other variables. **Figure 1** illustrates the effect of Edulastic at the two grade bands with 95% confidence intervals.

Figure 1: *Impact of Edulastic on Math Growth*



Note: *Non-Edulastic users are coded as 0 on the x-axis; Edulastic users are coded as 1. The R package that produces the plot centers all non-focal predictors (Long, 2019).*

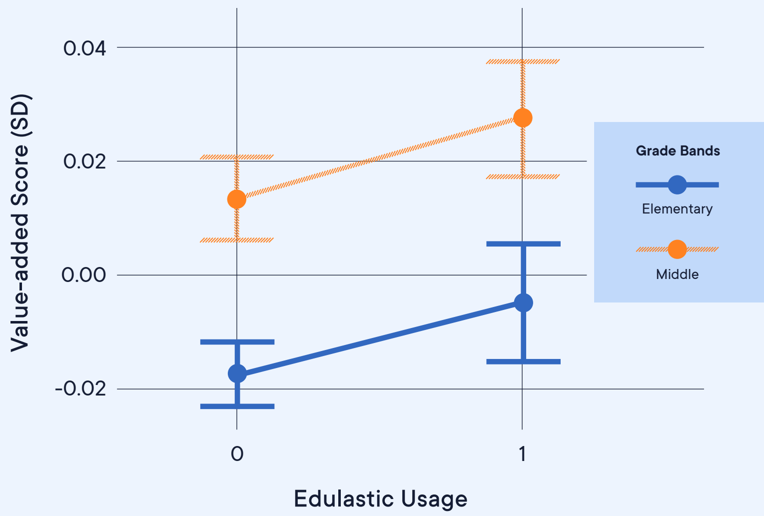
[1] We do not include the percentage of white students, as this would result in perfect multicollinearity.

Reading Findings

For the reading model, (see Table 3 in the appendix for full model results) the simple effect of assessments is significant, ***indicating that the use of Edulastic has a positive impact on reading growth in grades 4-8*** ($b = 0.011$, $SE = 0.004$, $p < 0.05$). The model estimate for assessments ($b = 0.011$) can be interpreted as an effect size.

The significant effect of grade band ($b = 0.033$, $SE = 0.003$, $p < 0.001$) indicates that middle school students had a higher average value-added score compared to elementary students while controlling for other variables. **Figure 2** illustrates the effect of Edulastic at the two grade bands with 95% confidence intervals.

Figure 2: *Impact of Edulastic on Reading Growth*



Note: *Non-Edulastic users are coded as 0 on the x-axis; Edulastic users are coded as 1. The R package that produces the plot centers all non-focal predictors (Long, 2019).*

Conclusion

In this correlational study, we employed multilevel models to account for the nested data structure and control for selection bias. To align the study with publicly available data at the grade-by-school level, the Edulastic usage variable necessarily had to be aggregated at the same level. The drawback of this approach was a less exact measure of Edulastic usage.

Edulastic usage encompasses a range of engagement with Edulastic's products, including grades in schools that rarely use the product with those that use it commonly. Despite this coarse measure of Edulastic usage, ***the results strongly suggest that Edulastic is beneficial for student learning as measured on standardized state assessments in Ohio in grades 4-8, with somewhat stronger evidence for its efficacy as a math intervention.***

References

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Table 2: *Math Model*

Value-added Score (SD)			
Predictors	**Estimates**	**CI**	**p**
(Intercept)	0.026	0.013 – 0.039	<0.001
assessments [1]	0.014	0.005 – 0.024	0.004
grade band [Middle]	0.042	0.035 – 0.048	<0.001
perc black	-0.128	-0.150 – -0.105	<0.001
perc hispanic	-0.075	-0.136 – -0.014	0.015
perc disabled	-0.119	-0.199 – -0.039	0.003
perc free_lunch	-0.008	-0.027 – 0.010	0.386

Random Effects	
σ^2	0.04
$\tau_{00\ school}$	0.01
ICC	0.21
N_{school}	2233
Observations	22,426
Marginal R^2 / Conditional R^2	0.041 / 0.245

Table 3: *Reading Model*

Value-added Score (SD)			
Predictors	**Estimates**	**CI**	**p**
(Intercept)	0.016	0.006 – 0.027	0.002
assessments [1]	0.011	0.002 – 0.019	0.013
grade band [Middle]	0.033	0.028 – 0.039	<0.001
perc black	-0.076	-0.093 – -0.058	<0.001
perc hispanic	-0.033	-0.081 – 0.015	0.178
perc disabled	-0.046	-0.108 – 0.017	0.152
perc free_lunch	-0.021	-0.036 – -0.007	0.003

Random Effects	
σ^2	0.02
$\tau_{00\ school}$	0.01
ICC	0.22
N_{school}	2233
Observations	22,498
Marginal R^2 / Conditional R^2	0.033 / 0.250