Progress Learning

McREL Research Summary

The Impact of the Progress Learning Platform on Sixth Grade Mathematics Achievement

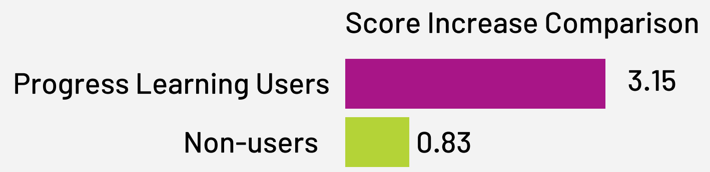
About the Research

McREL International conducted a rigorous, external evaluation of the impact of the Progress Learning platform on sixth grade mathematics achievement, using a quasi-experimental (matched comparison) design, which is aligned to Every Student Succeeds Act (ESSA) evidence standards for providing Tier 2 Moderate Evidence. The outcome of interest was scaled scores of sixth grade students on the mathematics subscale of the Florida Standards Assessments (FSA). Mathematics achievement of Progress Learning user schools was compared to non-user schools from the 2019 FSA administration, controlling for prior achievement and other school-level demographic variables from 2018, to ensure baseline equivalence of the two groups. Schools in the study displayed the minimum recommended level of usage.

Impact Results

McREL's research found that schools using Progress Learning had their FSA scores in sixth grade math grow by a substantially larger amount than those of non-user schools.

Progress Learning schools' scores increased by 3.15 points, compared with an increase of 0.83 points for non-user schools.



Progress Learning schools' growth was 280% larger than that of the non-user schools. McREL concluded that, "If schools purchase Progress Learning and implement it under similar conditions as schools included in this study, positive impacts may be found on mathematics achievement over the course of one school year of implementation."

This quick summary provided by Progress Learning, LLC
View the attached McREL Research document for full review.

The Impact of Progress Learning on Sixth Grade Mathematics Achievement

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Study Overview

The purpose of this study was to conduct a rigorous, external evaluation[1] of the impact of Progress Learning on sixth grade mathematics achievement using a quasi-experimental (matched comparison) design, which is aligned to Every Student Success Act (ESSA) evidence standards for providing Tier 2 Moderate Evidence. The outcome of interest was scaled scores of sixth grade students on the mathematics subscale of the Florida Standards Assessments (FSA). Mathematics achievement of Progress Learning user schools was compared to that of non-user schools from the 2019 FSA administration, controlling for prior achievement and other school-level demographic variables from 2018 to ensure baseline equivalence of the two groups.

Progress Learning user schools and non-user comparison schools were selected based on the following criteria:

1. Progress Learning user schools acquired the Progress Learning license for mathematics between October 2014 and November 2018 and demonstrated minimal usage of the resource defined as the completion of at least five activities per student.
2. Non-user schools were selected using a propensity score matching algorithm that accounted for baseline (2017-2018 school year) mathematics achievement and demographic characteristics to ensure that user and non-user schools were equivalent prior to the 2018-2019 intervention year.

Results of the study revealed a positive impact of Progress Learning on 2019, grade 6 achievement on the mathematics subscale of the FSA compared to non-user matched comparison schools, with a statistical significance level (p-value) of 0.02 and a Hedge's g effect size of 0.19.

Progress Learning Platform Description

Progress Learning, LLC is a nationwide provider of state standards-aligned curriculum resources and assessments that serves more than 4,000 schools, 85,000 teachers, and two million students through a comprehensive teaching platform for grades K-12. The Progress platform delivers teacher-written, standards-aligned content with daily tools for the creation of diagnostic, formative, and summative assessments, progress monitoring, and remediation. It includes three learning models – classroom mode, assessment mode, and personalized learning mode – affording teachers flexibility to decide when and how to use the resources in a way that complements their classroom instructional style. The platform includes both pre-built and build-your-own assessments for diagnostic, formative, and summative use, along with standards-aligned videos, games, projector questions, vocabulary worksheets/flashcards, interactive puzzles, bell-ringer questions, items of the day, and more. Students can move through the material at their own pace, thereby benefitting from differentiated instruction. Teachers, administrators, and students have the benefit of being able to review progress and observe growth on each standard.

Research Design: Quasi-Experimental Study

The current study aimed to answer the following research question:

- Did sixth grade students in schools that used Progress Learning show higher mathematics achievement on the 2019 FSA than their peers in matched comparison schools that did not use Progress Learning?

This research question was answered via secondary analysis of the FSA publicly available grade 6 data for Progress Learning user schools and non-user schools. Specifically, McREL conducted an analysis of sixth grade performance data from the 2017-2018 and 2018-2019 school years using a matched comparison quasi-experimental design. This type of design is listed in ESSA standards as appropriate for meeting Tier 2 standards for moderate evidence because it controls for any bias in impact estimates that may be due to baseline differences between users and non-users related to prior achievement and other demographic factors highly correlated with achievement.

Potential bias resulting from school self-selection as Progress Learning users was controlled with a rigorous matching strategy called Propensity Score Matching (PSM) – a computer-based algorithm that minimizes the overall distance between groups of cases (Rosenbaum & Rubin, 1985). Using this strategy, schools serving grade 6 that adopted and engaged in minimal usage of Progress Learning during the 2018-2019 school year were matched to other schools serving grade 6 students throughout the state of Florida that did not adopt the program and were not previous Progress Learning users. The literature on quasi-experimental studies suggests that matching based on pre-treatment measures of the eventual outcome of the study – in this case, mathematics achievement – is a key variable for optimizing matching and controlling bias. Thus, McREL used the prior year's (2017-2018) school-level achievement data from grade 6 to match the schools. In addition to prior achievement, McREL used the following demographic variables for matching on the basis of their relationship to student achievement:

- School size
- School locale (rural/non rural)
- School racial/ethnic composition (percentage of minority students)
- Percentage of students from families of low-socio-economic status as indicated by free- or reduced-priced lunch status
- Percentage of students with limited English proficiency (LEP)
- Percentage of students with disabilities
- Percentage of gifted students

Sample Selection and Power

The treatment sample included 34 schools in Florida serving grade 6 that acquired Progress Learning between October 2014 and November 2018 and demonstrated minimal usage defined by Progress Learning as the completion of at least five activities per student during the 2018-2019 (outcome) school year. The number of activities completed per student was calculated by dividing the school's total activities completed by sixth grade students by the number of sixth grade students tested on the mathematics subscale of the 2019 FSA.

A preliminary power analysis using Optimal Design software[1] (Spybrook, Bloom, Congdon, Hill, Martinez, & Raudenbush, 2011) indicated that a total of approximately 300 schools (including user and non-user schools) would be needed for a minimum detectable effect size[2] of 0.25. In order to approach this threshold with 34 treatment schools, a 1:6 propensity score matching procedure was used, which resulted in a total of 235 study schools (34 users and 201 non-users – see more about the matching strategy in the Propensity Score Matching Section below and in Appendix A).

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1 The following assumptions were made based on the educational literature (Cook, 2005; Hedges & Hedberg, 2007ab): (1) the value of significance level is 0.05; (2) variances explained by school-level variables (e.g., average school-level pretest for sixth grade, percentage of free and reduced lunch students, percentage of minority students, etc.) is 0.50, and the desired power is 0.80.

2 The minimum detectable effect size (MDES) represents the smallest true effect, in standard deviations of the outcome, that is detectable for a given level of power and statistical significance.

Propensity Score Matching

Matching was conducted using logistic regression to obtain a propensity score representing the probability that a unit with certain characteristics was assigned to the Progress Learning user group. After propensity scores were estimated, a one-to-six nearest neighbor matching algorithm without replacement was used to identify six non-user comparison schools per user school based on the aforementioned list of demographic and achievement variables (see Appendix A for more detail of PSM methods). Baseline characteristics of the Progress Learning user and non-user schools for the final[3] (post-matching) sample are shown in Table 1 . Analysis of variance did not reveal any statistically significant baseline differences between user and non-user schools on any of the variables (all *ps* > .40).

Table 1. Comparison of Progress Learning (User) and Comparison (Non-user) Schools 2018 Baseline (Post-matching) Characteristics for the Final Sample[a]

2018 School Characteristic	Progress Learning (User) Schools (N = 34)	Comparison (Non-user) Schools (N = 201)
	Mean (SD)	Mean (SD)
Mathematics achievement – FSA mean scaled scores	321.88 (8.83)[b]	322.44 (9.60)
School Size	959.62 (397.56)	959.63 (326.34)
	Percent	Percent
Percentage of rural schools	5.89%	5.97%
Percentage of racial/ethnic minority students	55.19%	54.84%
Percentage of students in the free- or reduced-price meal program	55.99%	56.50%
Percentage of students with limited English proficiency	5.76%	5.82%
Percentage of students with disabilities	18.73%	18.25%
Percentage of gifted students	8.61%	7.82%

a There were no statistically significant differences between Progress Learning user and non-user schools on any of the pre-intervention, post-matching school characteristic variables according to Analysis of Variance (all ps > .45).
b Numbers in parentheses are standard deviations.

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3 Effect sizes for each of the baseline covariates were calculated and presented in Appendix A.

Data Analysis

A single-level multiple linear regression model was used to examine the impact of Progress Learning on grade 6 mathematics achievement. All variables used in the matching process, including FSA mathematics achievement and demographic characteristics of schools from the prior school year (2017-2018), were entered in the model for control purposes. Weights from the PSM were also included to account for the 1:6 matching ratio without replacement. The full conditional analytic model used to analyze the impact of Progress Learning on school level achievement is specified in Appendix B. Prior to conducting the impact analysis, McREL examined the FSA mathematics scale scores from the baseline (2017-2018) year to check for baseline equivalence. Specifically, descriptive statistics (unadjusted means and standard deviations) were calculated along with linear regressions and effect sizes (Hedge's g) to ensure that the Progress Learning user schools were equivalent to non-user schools on mathematics achievement prior to the implementation year. Results from the baseline equivalence and impact analyses are described next.

Results

Baseline Equivalence

The first step in the analysis was to establish baseline equivalence by computing descriptive, regression, and effect size statistics on the grade 6 (2018) mathematics FSA scale scores. Results are presented in Table 2. The mean difference at baseline was negative 1.31, meaning the Progress Learning schools scored slightly lower than the non-user schools at baseline (2018). This difference according to the linear regression analysis was not statistically significant (*p* = 0.896). The effect size of negative 0.06 falls between negative 0.05 and negative 0.25, which, according to WWC (2017), requires statistical adjustment to satisfy baseline equivalence. It should be noted, however, that the difference between Progress Learning user schools and non-user schools is in the opposite direction of what was hypothesized for the results of the outcome analysis (e.g., non-user schools scored slightly higher than user schools at baseline). Regardless, the impact analysis included baseline (2018) scale score mathematics achievement along with several other demographic variables as covariates in the analytic model, which satisfies the WWC baseline equivalence requirement (see Data Analysis section).

Table 2. Results of baseline equivalence analyses for 2018 Grade 6 Mathematics FSA Scores

Analysis	Progress Learning (User) Schools			Comparison (Non-user) Schools			Mean difference	Test Statistic (*t*-value)	Significance Level (*p*-value)	Effect size (Hedge's *g*)
	Unadjusted Scale Score Mean	SD	N	Unadjusted Scale Score Mean	SD	N				
Baseline Equivalence	321.88	8.83	34	322.44	9.60	201	-.131	-0.32	0.750 [a]	-0.06 [b]

a p-value does not approach statistical significance.
b effect sizes > 0.05 to ≤0.25 satisfy baseline equivalence with statistical adjustment according to the WWC (2017).

Impact Analysis

Results of the impact analyses on grade 6 mathematics FSA achievement can be seen in Table 3.

Table 3. Results of impact analyses for 2019 Grade 6 Mathematics FSA Scores

Analysis	Progress Learning (User) Schools			Comparison (Non-user) Schools			Mean difference	Test Statistic (*t*-value)	Significance Level (*p*-value)	Effect size (Hedge's *g*)
	Adjusted Mean [a]	SD	N	Adjusted Mean [a]	SD	N				
Impact	325.03	9.32	34	323.27	9.60	201	-.131	-0.32	0.750	-0.06

a Means are adjusted for covariates in the regression model.
b *p*-values ≤ 0.05 are considered statistically significant.

For grade 6 mathematics, Progress Learning user schools showed an adjusted mean scale score of 325.03 in 2019 compared to an adjusted mean scale score of 323.27 for non-user schools. This adjusted mean difference of 1.76 scale score points was statistically significant ($p = .02$), with an effect size of .19.

Conclusions and Recommendations

This study was conducted to estimate the impact of the Progress Learning on grade 6 mathematics. Results of the study suggest that if schools purchase Progress Learning and implement it under similar conditions as schools included in this study, positive impacts may be found on mathematics achievement over the course of one school year of implementation. The impact analysis on mathematics achievement was conducted in the context of a quasi-experimental (matched comparison) design to establish baseline equivalence between Progress Learning user schools and non-user schools. As a result, the analyses provided an unbiased estimate of the impact of Progress Learning on grade 6 mathematics achievement.

An important factor to consider when interpreting these findings is that, while Progress Learning is typically implemented under real-world conditions (schools/districts purchase the intervention and implement it without requirements), only those schools that implemented the program in a way that approached or reached the developer's minimal usage standard were included in the study. Therefore, the results may not generalize to districts/schools that purchase the resource and do not use it at the level recommended by the developer.

Given these promising findings, Progress Learning is well positioned to expand both the scope and scale of research to support their product. Recommended next steps for research include expanding to additional states, grade levels, and content areas; exploring longitudinal trends across multiple years of usage; and conducting a randomized controlled trial where schools are randomly assigned to use Progress Learning to conform with the highest level of evidence standards.

McREL also recommends that Progress Learning engage in research to learn more about program implementation. Specifically, there are many aspects of the Progress resource, suggesting that it is a flexible tool that teachers can use in various ways. Learning more about implementation will provide Progress Learning with valuable information about which aspects of the program are being implemented most frequently and consistently, which aspects could use refinement or additional mechanisms to support sound implementation, and ultimately, how the various elements of the program work independently or in concert to support student learning.

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Appendix A:
Propensity Score Matching Procedure and Results

McREL researchers used publicly available data[4] to identify matched comparison schools for the Progress Learning user schools using propensity score matching (PSM). The original dataset included 112 schools that had current Progress Learning licenses during the 2018-2019 school year, and 3147 potential comparison schools that never had a Progress Learning license during or before the 2018-2019 school year. Because PSM does not allow missing data, schools with missing data on key covariates as well as the 2019 student achievement data were removed from the matching. After data cleaning, 91 Progress Learning schools and 970 potential comparison schools remained. Across the Progress Learning schools, the level of program usage varied widely. For this study, school level usage is measured by the average number of math activities completed by sixth grade students. After consulting with the program developer, McREL used the cut off of five activities per student to identify the Progress Learning user schools. This decision resulted in 34 treatment and 970 potential comparison schools remaining in the study sample for PSM.

Matching was done using logistic regression to obtain a propensity score representing the probability that a unit with certain characteristics was assigned to the Progress Learning user group. After propensity scores were estimated, a one-to-six nearest neighbor matching algorithm with a caliper of 0.25 and without replacement was used to identify six comparison schools per user school based on a list of demographic and achievement characteristics (i.e., covariates) that were found to be associated with the outcome of interest. Table A-1 shows the list of covariates that were included in the matching, including school-level demographic characteristics and grade-level specific student achievement score at baseline (i.e., 2017-18 school year).

Table A-1. Covariates included in propensity score matching and subsequent impact analyses

Covariate	Definition	Variables included in the matching
School locale	Rural vs. non-rural schools	RURAL
School size	Student enrollment	SchSize
Percentage of racial/ethnic minority students	Percentage of students who are from racial/ethnic minority groups	Minority
Percentage of students in the free or reduced-lunch meal program (FRL)	Percentage of students in the FRPM program	FRL
Percentage of students with limited English proficiency	Percentage of students with LEP	SchLEP
Percentage of students with disabilities	Percentage of students with disabilities	Disable
Percentage of gifted/talented students	Percentage of students who are gifted or talented	Gifted
School-level student achievement score	School mean of six grade students' mathematics test scores in the 2017-18 school year.	Math2018

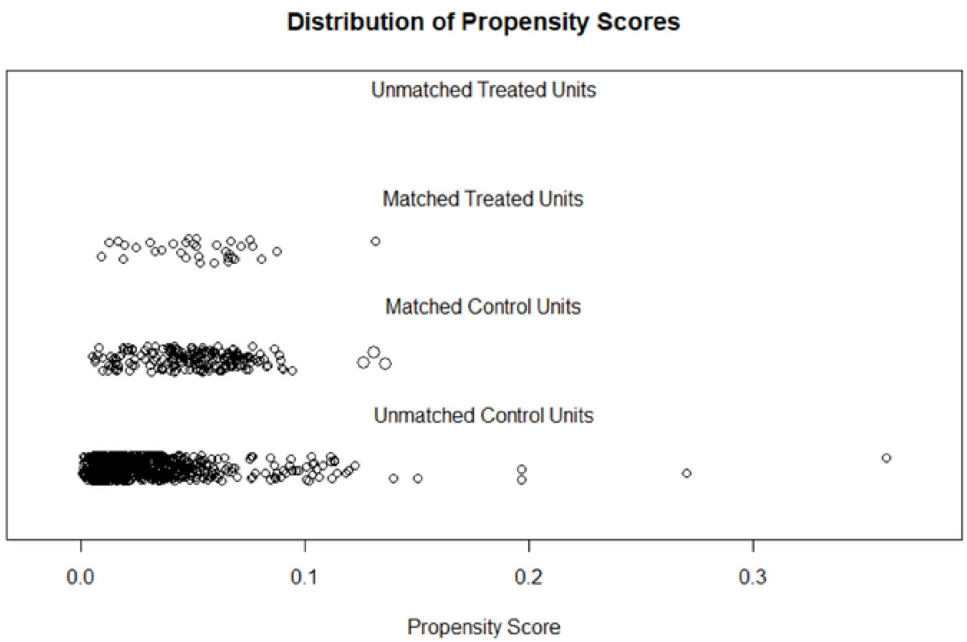
4 School-level demographic data were obtained from the Stanford Education Data Archive version 4.1 (SEDA) (https://edopportunity.org/get-the-data/seda-archive-downloads/). School-level student achievement data were obtained from the Florida Department of Education (http://www.fldoe.org/).

After the matching process was complete, balance diagnostics were conducted to check the quality of the matches. It was expected that the selected comparison (non-user) group would be similar to the user group on all covariates being used for the PSM process (Rubin, 2001). As shown in Figure B1, an examination of the distribution of propensity scores was first conducted to assess common support via a graphic diagnostic; then, three numerical balance measures were used to check covariate balances (Rubin, 2001):

- The ratio of the variances of the propensity scores in the two groups must be close to 1.0. Rubin (2001) suggests that the variance ratios should be between 0.5 and 2.0.
- The difference in the means of the propensity scores in the two groups being compared must be small. Rubin (2001) suggests that the standardized differences of means should be less than 0.25.
- For the percent of balance improvement[5], the larger the percent, the better the PSM results.

The result of PSM identified 201 matched comparisons for 34 Progress Learning user schools. A visual examination of Figure A-1 suggests that the selected comparison schools and Progress Learning user schools have similar distributions of propensity scores. As shown in Table A-2, the ratio of the variances of the propensity scores equals 1.02, which is within the range suggested by Rubin (2001). The analyses of standard mean differences suggest that the matching procedures have significantly minimized the group mean differences between the treatment and comparison schools across all four datasets. Most importantly, after the PSM process, all covariates had a standardized mean difference smaller than 0.25, as suggested by Rubin (2001). Results of the percent of balance improvement suggests that PSM, overall, improves the balance between the Progress Learning user and comparison schools, especially for the covariates that had a larger standardized mean difference before matching. For the covariates that had a small standardized mean difference before matching, the percent of balance improvement seems to be smaller or in some cases had negative values. This is expected because PSM decreases the standardized mean difference between user and comparison schools; hence, for the covariates that already have small standardized mean differences before the matching, the change in balance is likely to be small.

Figure A-1. Jitter plots of the distribution of propensity scores by groups



5 The percent improvement in balance is defined as 100*((|a| - |b|) / |a|), where a is the balance before and b is the balance after matching.

Table A-2. Balance Diagnosis Before and After the PSM Process: 6th Grade Math

Variables	Treatment				Comparison				Balance Diagnosis			
	Before		After		Before		After			Standard Mean Differences		
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	Variance Ratio	Before	After	% Balance Improvement
Propensity Score	0.05	0.02	0.05	0.02	0.03	0.02	0.05	0.02	1.02	0.78	0.04	94.4
Rural	0.06	0.24	0.06	0.24	0.16	0.37	0.06	0.24		-0.43	0.00	100.00
SchSize	959.62	397.56	959.62	397.56	789.41	401.47	959.63	326.34		0.43	-0.01	98.3
White	0.45	0.25	0.45	0.25	0.41	0.29	0.45	0.24		0.13	-0.02	82.4
FRL	0.56	0.18	0.56	0.18	0.56	0.24	0.57	0.19		0.00	0.02	-855.0
SchLEP	0.06	0.05	0.06	0.05	0.08	0.09	0.06	0.05		-0.53	0.00	99.7
Disable	0.18	0.05	0.18	0.05	0.17	0.09	0.18	0.05		0.19	0.03	86.0
Gifted	0.09	0.05	0.09	0.05	0.07	0.08	0.06	0.06		0.27	0.11	60.0
Math2018	321.88	8.83	321.88	8.83	325.05	13.15	322.44	9.60		-0.36	-0.06	83.0

Note. See Table A-1 for variable definitions.

Appendix B: Analytic Model for Impact Analyses

The full conditional analytic model used to analyze the impact of Progress Learning on school level achievement gains for both mathematics and reading is specified as:

$$Yi = \pi_0 + \pi_1 (TREAT)_i + \left(\sum_{S>0} \pi_{si} X_{si}\right) + \varepsilon_i$$

where:

Y_i = the gain outcome for school i,

π_0 = the regression-adjusted mean value of gain outcome for school i,

π_{1i} = is the adjusted mean difference in the school gain outcome between Progress Learning user schools and non-user schools,

TREAT = an indicator variable for the intervention coded as 1 for Progress Learning users schools and 0 for non-user schools,

π_{si} = the value of the coefficient on the sth school-level covariate (baseline achievement, percent of student qualifying for free-reduced priced lunch, percent minority students etc.),

X_{si} = the value of the sth school-level covariate for school i, and

ε_i = the residual error for school i which is assumed to be independently and identically distributed.