Efficacy Study of Imagine Learning Illustrative Mathematics in Iowa City Community School District

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EXECUTIVE SUMMARY

In this quasi-experimental design (QED) study, we examined the impact of the Imagine Learning Illustrative Mathematics (ILIM) program on Grades K-5 student math achievement in the Iowa City Community School District (ICCSD). The QED design compared students in classrooms that used ILIM with matched-comparison students in classrooms that did not use ILIM. Students were matched at the classroom level on the basis of prior achievement and demographic variables.

- The analytic ILIM and comparison groups consisted of 1,834 and 2,618 students, respectively, across all three outcome measures.
- Data sources included FastBridge earlyMath and aMath scores, and ISASP math scores.
- Impact analyses showed directionally positive impacts of ILIM on FastBridge earlyMath and aMath scores, with treatment students outperforming matched-comparison students by more than 2 points on earlyMath and by 0.5 points on aMath. Effect sizes for these impacts were .10 *SD*s and .04 *SD*s for earlyMath and aMath, respectively.
- Subgroup analyses showed significant positive impacts of ILIM for SPED and Black students on earlyMath scores, and for Grade 3 and SPED students on aMath scores.

INTRODUCTION

Overview of Illustrative Mathematics

As described by the provider, Imagine Learning Illustrative Mathematics is a problem-based math curriculum comprising both print and interactive digital materials. Lessons include five core structural components:

1. Lesson Warm-Ups
2. Lesson Instructions and Activities
3. Lesson Synthesis
4. Lesson Cool-Downs
5. Centers (K-5 only)

Each unit also includes pre-assessments, problem checkpoints, and practice problems for students to engage in, and the curriculum includes end-of-unit, and end-of-course assessments. Teachers shape lesson plans to meet their students' learning needs and use assessments to monitor student progress.

Imagine Learning provided the Imagine Learning Illustrative Mathematics curriculum and professional learning for ICCSD teachers during the summer of 2023. Technical assistance to support teacher implementation was provided throughout the 2023-24 school year, in addition to other professional development.

Overview of the Evaluation

In June of 2025, Imagine Learning contracted with the Center for Research and Reform in Education (CRRE) at Johns Hopkins University to conduct a quasi-experimental design (QED) study of Imagine Learning's Illustrative Mathematics program. This study examined student performance on the FastBridge math assessments and the Iowa Statewide Assessment of Student Progress (ISASP). It is important to note that, while CRRE did not conduct analyses until the summer of 2025, this was not a retrospective study, as identification of treatment and comparison conditions was determined prior to implementation.

The study used a quasi-experimental design to examine these research questions:

1. How does the math performance of students who used ILIM compare to that of a similar group of students who did not use the program?
2. Is ILIM differentially beneficial for students with varying demographic profiles (e.g., gender, race/ethnicity, socioeconomic status, English-language classification, special education classification, free or reduced-priced lunch status, and prior achievement?

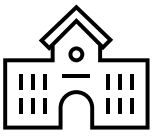
METHOD

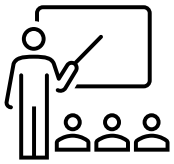
Research Design

This study examined the efficacy of ILIM by conducting a quasi-experimental design on Grades K-5 students during the 2023-24 school year. Grades 6-8 students were initially included in the study design, but due to large amounts of missing data in these grade levels, they were excluded from the main study. Impact analyses examined differences in math score growth patterns for students of teachers that used ILIM and matched-comparison students in classrooms that did not use ILIM. Subgroup analyses were also conducted to examine potentially differential patterns of program impacts across student sub-populations of interest (i.e., SPED, FARMS, race/ethnicity).

Participants

Details about study participants are presented below. Note that the current QED design was conducted at the classroom level; thus, schools could have a mix of treatment (ILIM) and comparison (business-as-usual) classrooms. In interpreting the condition descriptions below, this means that 16 elementary schools contained at least one treatment classroom, while 22 elementary schools contained at least one classroom that did not use ILIM.

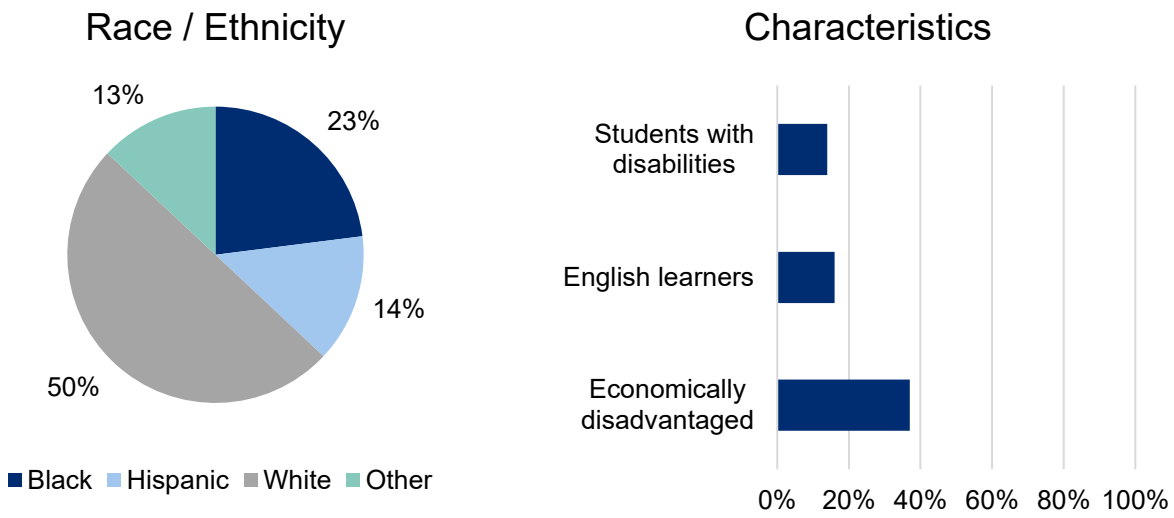




Treatment group	16 schools	1,834 Grades K-5 students	80 teachers[1]
Comparison group	22 schools	2,618 Grades K-5 students	110 teachers

[1] A total of 83 sections were taught by 80 teachers; 3 teachers taught 2 sections each of math.

Demographic snapshot of student participants[2]



The study took place in the Iowa City Community School District (ICCSD). ICCSD is a small- to medium-sized urban district that serves nearly 15,000 students across 29 schools. Demographics of the analytic sample are presented in Table 1. Note that Table 1 includes all students included in at least one of the three matched analytic samples (earlyMath, aMath, and ISASP Math; discussed in more detail below).

Table 1
Demographics of Analytic Sample

	Treatment %	Matched Comparison%
Female	47.55	48.17
Black	22.08	23.41
White	49.56	50.76
Hispanic	14.78	12.99
Other Race/Ethnicity	13.58	12.83
SPED	15.27	12.80
ELL	16.58	15.51
FARMS	41.82	34.38
N	1,834	2,618

No significant differences between the treatment and matched-comparison students were observed on any demographic variables. Approximately half of the students in both conditions were White, followed by Black and Hispanic students. Slightly more treatment students were classified as economically disadvantaged (FARMS), while approximately 15% of students in both conditions were classified as English language

[2] Data provided by ICCSD.

learners (ELL) or special education (SPED).

Measures

To address the research questions, the study team analyzed FastBridge math scores from fall 2023 and spring 2024, as well as ISASP math scores from spring 2023 and spring 2024. Demographic data were analyzed as both control variables in impact models and for subgroup analyses.

Data sources and measures for the current study included student achievement, demographics, and rostering variables, as described below.

FastBridge earlyMath and aMath. FastBridge earlyMath (Grades K-1) and aMath (Grades 2-5) scores from the beginning of the year (BOY) and end of the year (EOY) of the 2023-24 school year were used. The earlyMath assessment is aligned with National Common Core State Standards and covers the domains of number sense (number, relations, and operations). FastBridge aMath is based on recommendations of the National Math Panel and National Common Core State Standards and can be administered to all Grades K-12 students, though ICCSD starts administering aMath in Grade 2. Both earlyMath and aMath scores are vertically scaled so that students across grade levels can be directly compared to each other; however, aMath is a computer adaptive assessment while earlyMath is not. Thus, each sample (K-1 for earlyMath, 2-5 for aMath) was considered separately.

It is important to note that ICCSD provided FastBridge aMath scores for Grades 2-8 students. However, over half of the treatment sample in Grades 7 and 8 were missing EOY aMath scores. After investigating with ICCSD, we discovered that one ICCSD middle school did not administer aMath in the spring of 2024.

ISASP Math. The ISASP math assessment is administered to all Grades 3-11 students in Iowa during the spring of each school year. ISASP is aligned with Iowa Core Standards and is a criterion-referenced assessment. The ISASP math test was administered digitally (non-computer adaptive) for the majority of ICCSD students in 2023-24, with paper copies provided only when required. ISASP assessment scores are vertically scaled.

Demographic and rostering data. ICCSD provided demographic and rostering data for all Grades K-8 students, even though we elected to analyze results for Grades K-5 students only in the main analyses for the 2023-24 school year. Demographic data included gender, race/ethnicity, and indicators for special education, English-learners, and economically disadvantaged. In addition, ICCSD provided rostering data including student grade level, school name, and math teacher. Math teacher identification was used to assign students to treatment (ILIM) and comparison (business-as-usual) conditions as described below.

Analytical Approach

Hierarchical Linear Modeling (HLM) with students nested within teachers nested within

schools was used to determine program impacts on FastBridge and ISASP score gains. In addition, Multiple Linear Regression (MLR) was used to model a set of secondary impact analyses at the student level, as opposed to the cluster (classroom) level. Demographic variables including gender, race/ethnicity, special education status, English-learner status, and economically disadvantaged status, as well as dummy variables for student grade levels, were included in all models. It is important to note that separate analyses were conducted for each outcome variable.

The treatment sample consisted of Grades K-5 classrooms that used ILIM. To identify similar classrooms that did not use the program, propensity score matching (PSM) was used to create comparison groups of students that were as similar as possible to treatment classrooms that used the program. These analyses were conducted at the classroom level and for each analytic sample (earlyMath, aMath, and ISASP). Propensity scores were computed using the psmatch2 command in Stata (v 18.0); one-to-one nearest neighbor matching without replacement was used for all samples, classroom-level prior math achievement and demographic variables were included in the matching procedure. Using these PSM procedures, treatment classrooms were matched with comparison classrooms that were as similar as possible in prior math achievement and demographic variables. This allowed for a more rigorous contrast of treatment and comparison students. The matched samples demonstrated baseline equivalence overall and across all grade levels. Overall baseline equivalence estimates for all analytic samples can be found in Table 2. After PSM was applied to all samples, standardized mean differences were at or below .10 *SD*s, well below the What Works Clearinghouse 0.25 *SD* cutoff criterion.

Table 2
Baseline Equivalence, by Analytic Sample

Analytic Sample	All students	Treatment			Comparison			Standardized Mean Difference
	n	*n*	*M*	*SD*	*n*	*M*	*SD*	*M*
early-Math	1,089	533	45.27	28.63	546	46.06	28.55	-.03
aMath	2,429	1,209	208.16	11.80	1,220	208.12	12.27	.002
ISASP	1,263	577	423.33	40.39	686	419.51	39.22	.10

RESULTS

This section of the report begins with findings related to impact analyses examining the efficacy of ILIM on mathematics achievement by outcome variable. This will be followed by findings of subgroup analyses, again grouped by outcome.

Imagine Learning Illustrative Mathematics Achievement Impacts

RQ 1. How does the math performance of students who used ILIM compare to that of a similar group of students who did not use the program?

Key Findings

- A directionally positive impact was found on FastBridge earlyMath, with treatment students outperforming matched-comparison students by 2.1 points (effect size = .10).
- Similarly, a directionally positive impact was found on FastBridge aMath, with treatment students outperforming matched comparison students by .50 points (effect size = .04).
- A directionally negative impact was found on ISASP Math, with matched comparison students slightly outperforming treatment students by 1.3 points (effect size = -.03).

Achievement Impact Analyses

Analyses were conducted separately for each outcome (earlyMath: Grades K-1; aMath: Grades 2-5; ISASP: Grades 4 and 5[3]). All impact analyses were grand mean centered to enable interpretation of the intercept. The results are summarized in Tables 3-5.

Table 3
Impact Analysis of ILIM on Spring 2024 FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	2.076	1.411	.141	.10
Constant	69.417***	1.062	<.001	
Variance of Constant (Teacher)	4.078	2.859		
Residual of Constant	149.562	6.739		
Student *N*	1,040			
Teacher *N*	57			
School *N*	18			

*Note. *** p < .001.*

The analysis of FastBridge earlyMath scores for Grades K-1 students showed a directionally positive, though statistically nonsignificant program impact (see Table 3). The regression estimate ("ILIM") can be interpreted as the average difference in spring 2024 earlyMath scores between treatment and matched comparison students. Thus, treatment students outscored matched comparison students by more than 2 points on the earlyMath assessment. Although qualified by the nonsignificant outcome, the effect

[3] Grade 3 was not included in ISASP analyses, due to the lack of a prior ISASP score from the previous year.

size of .10 *SD*s is indicative of a medium practical impact of ILIM on earlyMath scores.

It is important to note that, in a MLR analysis that does not take into account clustering at the teacher and student level, the impact of ILIM on earlyMath scores becomes statistically significant, with ILIM students outscoring matched comparison students by an average of 1.6 points and an effect size of .08 *SD*s[4]. The results of this analysis (and all non-clustered MLR analyses) can be found in Appendix A.

Table 4
Impact Analysis of ILIM on Spring 2024 FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	0.502	0.322	.120	.04
Constant	213.260***	0.227	<.001	
Variance of Constant (Teacher)	1.835	0.400		
Residual of Constant	20.881	0.624		
Student *N*	2,360			
Teacher *N*	128			
School *N*	21			

*Note. *** p < .001.*

Similar to the earlyMath analysis, ILIM was shown to have a directionally positive, though statistically nonsignificant (p = .12) impact on FastBridge aMath scores for Grades 2-5 students. The regression estimate ("ILIM") can be interpreted similarly to that in the prior analysis. Thus, treatment students outscored matched-comparison students by one-half of a point on the spring 2024 aMath assessment. The effect size of .04 *SD*s is indicative of a small practical impact of ILIM on aMath scores.

Table 5
Impact Analysis of ILIM on Spring 2024 ISASP Math Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	-1.292	2.187	.555	-.03
Constant	441.800***	1.536	<.001	
Variance of Constant (Teacher)	43.186	12.664		
Residual of Constant	365.831	15.983		
Student *N*	1,104			
Teacher *N*	62			
School *N*	20			

*Note. *** p < .001.*

[4] This analysis and its results would qualify the study for providing "promising" (Tier 3) evidence of program effectiveness under ESSA guidelines.

The results of this analysis showed ILIM to have a small, directionally negative, and statistically nonsignificant, impact on spring 2024 ISASP scores for Grades 4-5 students. The regression estimate indicates that matched-comparison students outscored treatment students by 1.3 points on the ISASP math assessment. The small magnitude of the estimate (Effect Size = -.03) and the relatively large *p* value (*p* = .555) indicate that students in both conditions performed very similarly on ISASP math.

Subgroup Analyses

RQ 2. Is ILIM differentially beneficial for students with varying demographic profiles (e.g., gender, race/ethnicity, socioeconomic status, English-language classification, special education classification, free or reduced-priced lunch status, and prior achievement?

Key Findings

- A significant positive impact of ILIM on earlyMath scores for Black students (5.6 point advantage) and SPED students (8.5-point advantage).
- A significant positive impact of ILIM on aMath scores for Grade 3 students (1.3 point advantage) and SPED students (1.4 point advantage).
- No significant subgroup impacts were observed on ISASP Math scores.

In this section, we examine the results of subgroup analyses analyzing ILIM impacts on each of the three outcome variables in this analysis. For each demographic subgroup indicator, we created an interaction term that was the product of the subgroup indicator and the treatment variable. A significant interaction term indicated significant differences in the impact of ILIM on a particular student subgroup (i.e., SPED vs. non-SPED students). To examine simple effects of ILIM on each subgroup, we report the additive impacts of treatment main effect plus interaction term for each subgroup of interest, with Wald tests[5], performed on each simple effect. Complete regression tables related to subgroup analyses can be found in Appendices B-D. Tables 6-8 show the results of subgroup analyses on earlyMath, aMath, and ISASP, respectively.

Table 6

Subgroup Analysis Results, ILIM Impacts on Spring 2024 FastBridge earlyMath Scores

Subgroup	Estimate	*p* value	Effect Size	*n*
Grade K	2.032	.216	.09	529

[5] Wald tests are used to determine whether a parameter (in this case, the simple effect of treatment + treatment*subgroup interaction term) is significantly different from zero.

Grade 1	2.136	.242	.10	511
Black	5.582**	.007	.26	228
Hispanic	2.409	.348	.11	127
FARMS	1.516	.379	.07	406
ELL	2.274	.276	.11	211
SPED	8.500**	.001	.40	126

Note. ** $p < .01$.

Subgroup analytic models including interaction terms of treatment by student subgroup indicator variables revealed significant interactions between treatment and both Black and SPED indicator variables. Follow-up simple effects analyses showed that ILIM had a significant positive impact on earlyMath scores for Black students and SPED students ($p < .01$ for both groups). Specifically, Black treatment students outperformed Black comparison students by 5.6 points, while SPED treatment students outperformed SPED comparison students by 8.5 points. Effect sizes for these subgroups of .26 and .40 *SD*, respectively, indicate large practical program impacts for Black and SPED students. These results build on the results of the main earlyMath impact analysis by showing especially powerful impacts of ILIM on Black and SPED student math achievement.

Table 7

Subgroup Analysis Results, ILIM Impacts on Spring 2024 FastBridge aMath Scores

Subgroup	Estimate	*p* value	Effect Size	*n*
Grade 2	0.317	.616	.03	558
Grade 3	1.268*	.035	.11	640
Grade 4	0.418	.520	.03	580
Grade 5	-0.127	.847	-.01	582
Black	0.572	.253	.05	489
Hispanic	0.784	.188	.07	316
FARMS	0.354	.367	.03	1,024
ELL	-0.036	.954	.00	284
SPED	1.413*	.013	.12	340

Note. * $p < .05$.

Subgroup analytic models including interaction terms of treatment by subgroup indicator variables revealed no significant interactions, though the interaction between treatment and SPED approached significance ($p = .051$), with the positive value of the interaction term indicating larger program impacts for SPED students. Follow-up simple effects analyses showed that ILIM had significant positive impacts for Grade 3 students and SPED students ($p < .05$ for both groups). Specifically, Grade 3 treatment students outperformed Grade 3 comparison students by 1.3 points on aMath, while SPED treatment students outperformed SPED comparison students by 1.4 points. Effect sizes for these student subgroups were .11 and .12 *SD*s, respectively, indicative of moderate practical significance of program impacts for Grade 3 and SPED students. These results continue to build support for the efficacy of ILIM on student subgroups, especially special education students.

Table 8

Subgroup Analysis Results, ILIM Impacts on Spring 2024 ISASP Math Scores

Subgroup	Estimate	*p* value	Effect Size	*n*
Grade 4	1.665	.580	.04	542
Grade 5	-4.240	.157	-.09	562
Black	-0.943	.765	-.02	246
Hispanic	0.799	.829	.02	154
FARMS	0.230	.929	.01	489
ELL	6.947	.095	.15	111
SPED	2.034	.587	.05	144

Similar subgroup analytic models including treatment by subgroup interaction terms revealed a statistically significant interaction between treatment and ELL students. While the follow-up simple effect test was not significant for ELL students (p = .095), this directional impact, along with a medium effect size of .15 *SD*s, provides suggestive evidence of the efficacy of ILIM for ELL students. Across all subgroups, simple effects analyses showed nonsignificant results, though treatment students in these subgroups generally performed slightly better on ISASP math than did comparison students in the same subgroups.

DISCUSSION

The purpose of the present study was to evaluate the efficacy of ILIM in the Iowa City Community School District. Outcome measures included FastBridge earlyMath and aMath scores, as well as ISASP math scores. Findings from overall and subgroup impact analyses for each measure were presented in this report.

Main Impact Analyses

Results of the main impact analyses showed directionally positive impacts of ILIM on earlyMath and aMath scores, with treatment students outperforming matched-comparison students by 2.1 points on earlyMath and 0.5 points on aMath. Effect sizes of these impacts were .10 *SD*s on earlyMath and .04 *SD*s on aMath, indicative of small-to-medium practical impacts of ILIM on student math achievement. Additionally, student-level analyses were conducted that did not take into account teacher and school clustering. The impact of ILIM on earlyMath in this analysis was statistically significant (p = .042), with ILIM students outscoring matched-comparison students by 1.6 points. This result appears to meet criteria for ESSA Tier 3 (“Promising”) evidence.

Subgroup Analyses

Subgroup analyses showed significant positive ILIM impacts for several student subgroups on earlyMath and aMath. Specifically, ILIM had significant positive impacts for SPED and Black students on earlyMath and for Grade 3 and SPED students on aMath. No significant positive impacts of ILIM on ISASP were evidenced, though patterns of gains for ELL treatment students on ISASP were considerably more positive

as compared to those for the entire analytic sample. The results of these analyses overall provide evidence supporting the efficacy of ILIM for raising the math achievement of specific student subgroups, especially Black and special education students. To identify best practices in implementing ILIM overall and with particular subgroups we recommend conducting further mixed-methods evaluation research incorporating teacher perceptions of their experiences and impacts on students.

APPENDIX A: Student Level earlyMath Impact Analyses

Table A1

Impact Analysis of ILIM on Spring 2024 FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	1.625*	0.799	.042	.08
Constant	69.015***	0.558	<.001	
Student *n*	1,040			

*Note. * p < .05; *** p < .001.*

Table A2

Impact Analysis of ILIM on Spring 2024 FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	-0.297	0.359	.409	-.02
Constant	210.025***	4.732	<.001	
Student *n*	2,360			

*Note. *** p < .001.*

Table A3

Impact Analysis of ILIM on Spring 2024 ISASP Math Scores

Variable	Estimate	Standard error	*p* value	Effect Size
ILIM	-1.534	2.706	.571	-.04
Constant	417.796***	8.162	<.001	
Student *n*	1,104			

*Note. *** p < .001.*

APPENDIX B: Full Subgroup Regression Tables – earlyMath

Table B1

Grade Level Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM (Grade 1)	2.136	1.825	.242
ILIM*Grade K	-0.104	1.996	.959
Constant	69.412***	1.064	<.001
N	1,040		

Note. *** $p < .001$.

Table B2

Black Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.936	1.484	.528
ILIM*Black	4.645*	1.996	.020
Constant	69.489***	1.058	<.001
N	1,040		

Note. * $p < .05$; *** $p < .001$.

Table B3

Hispanic Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	2.031	1.440	.159
ILIM*Hispanic	0.378	2.434	.877
Constant	69.413***	1.062	<.001
N	1,040		

Note. *** $p < .001$.

Table B4

FARMS Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	2.468	1.585	.117
ILIM*FARMS	-0.951	1.695	.575
Constant	69.403***	1.059	<.001
N	1,040		

Note. *** $p < .001$.

Table B5

ELL Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	2.017	1.495	.174
ILIM*ELL	0.258	2.004	.898
Constant	69.424***	1.063	<.001
N	1,040		

Note. *** $p < .001$.

Table B6

SPED Subgroup Analysis of ILIM Impacts on FastBridge earlyMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	1.300	1.452	.370
ILIM*SPED	7.200**	2.393	.003
Constant	69.290***	1.076	<.001
N	1,040		

Note. ** $p < .01$; *** $p < .001$.

APPENDIX C: Full Regression Subgroup Tables - aMath

Table C1

Grade Level Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM (Grade 5)	-0.127	0.661	.847
ILIM*Grade 2	0.444	0.914	.627
ILIM*Grade 3	1.395	0.894	.119
ILIM*Grade 4	0.546	0.924	.555
Constant	213.263***	0.225	<.001
N	2,360		

Note. *** $p < .001$.

Table C2

Black Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.482	0.340	.156
ILIM*Black	0.090	0.491	.855
Constant	213.261***	0.227	<.001
N	2,360		

Note. *** $p < .001$.

Table C3

Hispanic Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.458	0.332	.168
ILIM*Hispanic	0.326	0.579	.573
Constant	213.258***	0.227	<.001
N	2,360		

Note. *** $p < .001$.

Table C4

FARMS Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.621	0.371	.094
ILIM*FARMS	-0.267	0.409	.514
Constant	213.258***	0.226	<.001
N	2,360		

Note. *** $p < .001$.

Table C5

ELL Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.579	0.331	.080
ILIM*ELL	-0.615	0.607	.311
Constant	213.2626***	0.226	<.001
N	2,360		

Note. *** $p < .001$.

Table C6

SPED Subgroup Analysis of ILIM Impacts on FastBridge aMath Scores

Variable	Estimate	Standard error	*p* value
ILIM	0.344	0.332	.300
ILIM*SPED	1.069	0.547	.051
Constant	213.257***	0.226	<.001
N	2,360		

Note. *** $p < .001$.

APPENDIX D: Full Subgroup Regression Tables - ISASP

Table D1
Grade Level Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM (Grade 5)	-4.240	2.996	.157
ILIM*Grade 4	5.905	4.219	.162
Constant	441.748***	1.501	<.001
N	1,104		

Note. *** $p < .001$.

Table D2
Black Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM	-1.396	2.291	.542
ILIM*Black	0.453	2.958	.878
Constant	441.808***	1.537	<.001
N	1,104		

Note. *** $p < .001$.

Table D3
Hispanic Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM	-1.647	2.239	.462
ILIM*Hispanic	2.446	3.474	.481
Constant	441.810***	1.532	<.001
N	1,104		

Note. *** $p < .001$.

Table D4
FARMS Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM	-2.556	2.468	.300
ILIM*FARMS	2.787	2.501	.265
Constant	441.844***	1.539	<.001
N	1,104		

Note. *** $p < .001$.

Table D5
ELL Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM	-2.246	2.218	.311
ILIM*ELL	9.193*	3.956	.020
Constant	441.835***	1.531	<.001
N	1,104		

Note. * $p < .05$; *** $p < .001$.

Table D6

SPED Subgroup Analysis of ILIM Impacts on ISASP Math Scores

Variable	Estimate	Standard error	*p* value
ILIM	-1.805	2.237	.420
ILIM*SPED	3.840	3.511	.274
Constant	441.786***	1.536	<.001
N	1,104		

Note. *** $p < .001$.