Quarterly Research Note

Accelerate
The National Collaborative for Accelerated Learning

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Introduction

Welcome to the fifth issue of the Quarterly Research Note (QRN), a research brief that reflects Accelerate's approach to learning what educational interventions work, for which students, and under what conditions.

In this issue, we revisit Accelerate's Tutoring Efficiency metric, which measures the tutoring dosage necessary to improve student learning. We present evidence on Tutoring Efficiency for a subset of Call to Effective Action (CEA) grantees whose tutoring programs significantly improved student learning during the 2023-24 school year.

In this issue's Research Roundup, we profile newly released evidence from the 2023-24 school year on the implementation and impact of tutoring from the Personalized Learning Initiative (PLI), a multi-year, multi-site experimental evaluation of tutoring to understand what models of tutoring work best for which students in which contexts, and at the lowest possible cost. We then profile one site-specific randomized controlled trial (RCT) from the PLI study which was designed and implemented to examine the impact of both a virtual tutoring intervention and an edtech intervention on middle school student math achievement.

In Looking Ahead, we profile Accelerate's newest grant programs to be launched in the 2025-26 school year: Evidence for Impact (EFI), which will focus exclusively on RCTs that are well-designed and well-powered to address specific evidence gaps identified in Accelerate's Research Agenda; and Call for Effective Technology (CET), which aims to identify and study the design, implementation, impact, and cost-effectiveness of Artificial Intelligence (AI) and tech-enabled tools.

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Part One

Revisiting Tutoring Efficiency

In May 2024, Accelerate introduced Tutoring Efficiency, a measure of the return on tutoring dosage in terms of student learning, which we define as the hours of tutoring to improve student learning by one month. Tutoring Efficiency enables not only an assessment of the return on tutoring time across program providers, but it is also an essential component for calculating a program's return on investment (i.e., cost-effectiveness). In Accelerate's companion February 2025 report, we introduced our cost analysis tool for collecting program-specific cost data necessary for calculating a program's cost-effectiveness.

In this section, we revisit the Tutoring Efficiency metric with new evidence from the 2023-24 school year on tutoring program impact from evaluation studies of Accelerate's Call to Effective Action (CEA) grantees. We present evidence on the distribution of Tutoring Efficiency among a subset of CEA grantees with statistically significant estimates of program impact from randomized controlled trials (RCTs) or quasi-experimental designs (QEDs). Table 1 describes the program characteristics of four CEA grantees, including subject, grade(s), tutor:student ratio, and modality. Table 1 also indicates the study's research design, outcome measure, the actual (mean) dosage students received, and the effect size (in standard deviation (SD) units).

Table 1. Tutoring Provider and Research Study Characteristics

Tutoring Provider	Subject	Grade(s)	Tutor:Student Ratio	Modality	Research Design	Outcome Measure	Dosage Received (hours)	Effect Size (SD)
Air Reading	Reading	1-6	1:3	Virtual	RCT	NWEA MAP	27	0.12
Air Tutors	Math	4-6	1:4	Virtual	QED (PSM)	Star Math	40	0.09
Ignite Reading	Reading	1	1:1	Virtual	QED (PSM)	DIBELS	32	0.21
KIPP Indy	Math	6-8	1:2	In-Person	RCT	NWEA MAP	8	0.23

Notes: *Dosage Received* indicates the mean hours of tutoring dosage that tutored students received during the study period. *RCT* indicates that the study was a randomized controlled trial (RCT); *QED(PSM)* indicates that the study was a quasi-experimental design that relied on a propensity score matched design. Air Tutors based on findings from one district ("District A") in Colorado; Air Reading based on findings from Terrell ISD (Texas); Ignite Reading based on findings from 13 school districts in Massachusetts; KIPP Indy based on findings from KIPP Indy Public Schools.

We focus on the following: (i) using actual (instead of intended) dosage for calculating Tutoring Efficiency; (ii) the sensitivity of Tutoring Efficiency to the benchmark for average annual growth in student achievement; and (iii) the sensitivity of Tutoring Efficiency to the magnitude of program impact and sampling variability. We conclude by posing some outstanding questions about the validity, precision, and comparability of the Tutoring Efficiency metric that remain to be pursued.

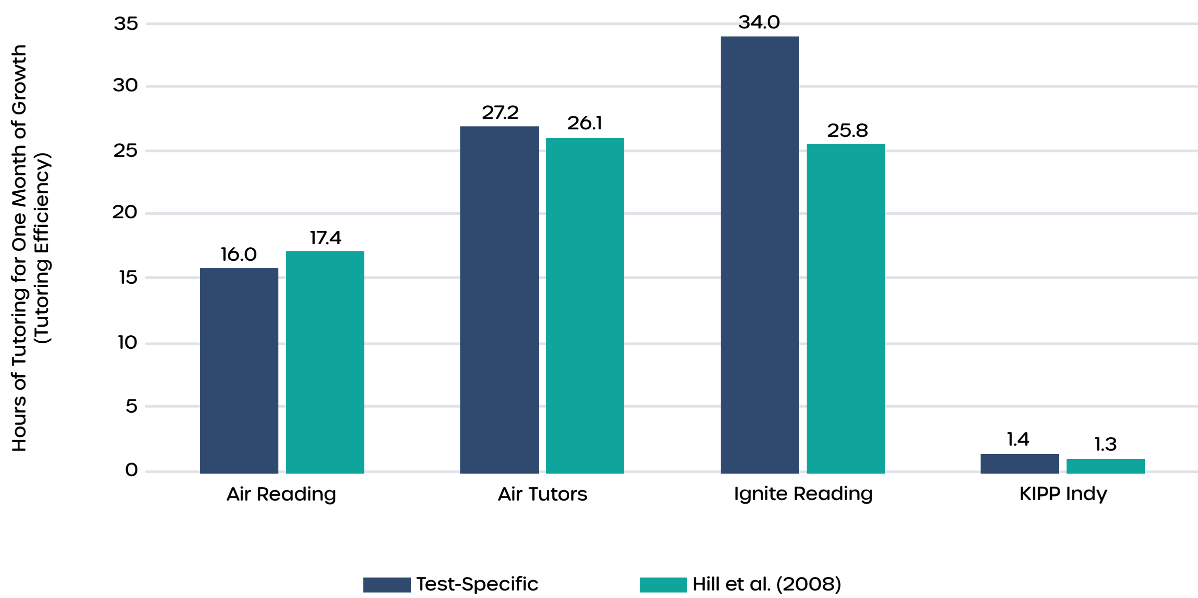
Accelerate's May 2024 report proposed using intended dosage to calculate Tutoring Efficiency, noting that the Tutoring Efficiency metric relies "on intended dosage because (i) it is more consistently reported than actual dosage; and (ii) it more accurately represents the amount of effort required to implement the program." In that retrospective analysis of tutoring program impacts included in the May 2024 report, intended dosage was more readily available and publicly reported than actual dosage, to the extent that intended dosage represents the total hours of tutoring dosage as defined by the program model. Yet, through Accelerate's work with our grantees and tutoring program providers, it has become clear that intended dosage is not consistently defined across programs and implementations. For example, some providers view intended dosage as the maximum tutoring hours available to students as defined by the program model, while other providers view intended dosage as the maximum tutoring hours that can be implemented in a given school setting with a fixed implementation duration (e.g., one semester versus two semesters). Further, the return on tutoring time, as measured by Tutoring Efficiency, is more accurately represented by the actual amount of tutoring dosage that students receive. Thus, mapping the actual dosage that students receive in the context of a program's implementation to the program impact estimate from that same implementation most accurately reflects the time necessary to improve student learning outcomes in the context of a given program implementation. All estimates of Tutoring Efficiency herein rely on actual dosage received during the program's implementation during the 2023-24 school year.[1]

Figure 1 presents Tutoring Efficiency estimates for the four tutoring programs by growth benchmark and the actual tutoring dosage students received during the program's implementation. Values of Tutoring Efficiency that are closer to zero are more efficient (in terms of time) at producing student learning gains. Figure 1 also enables assessment of the sensitivity of Tutoring Efficiency to the choice of the student growth benchmark, showing Tutoring Efficiency based on two benchmarks for the average annual growth in student achievement: (i) test-specific benchmark, which is the estimated average annual growth in student learning (by grade-level and subject area) based on the study's test-specific outcome measure (e.g., NWEA MAP; STAR); and (ii) summative benchmark from Hill et al. (2008), which is the estimated average annual growth in student learning (by grade-level and

[1] There are likely multiple measures required to fully define the scope of a program's tutoring dosage, including: (i) the total (maximum) hours of tutoring as defined by the program model, independent of a particular implementation setting (i.e., the capacity needed for full program implementation); (ii) the total hours of tutoring available to students in a specific implementation setting (i.e., the capacity available for program implementation based on school-specific factors such as scheduling); (iii) the minimum hours of tutoring a program deems necessary to improve student learning (i.e., adequate dosage); and (iv) the actual hours of tutoring that students receive in a given implementation setting.

subject area) based on a composite measure of expected student growth from multiple nationally-normed assessments of student achievement.[2] Results from Figure 1 indicate that there is variability across programs in their efficiency at producing student learning gains. For example, Air Reading requires an average of approximately 17 hours of tutoring to increase student learning by one month. It is important to note that estimates of Tutoring Efficiency are relevant for a particular implementation setting (we discuss this point below). Figure 1 also shows that estimates of Tutoring Efficiency are relatively insensitive to the choice of student growth benchmark, with the greatest variability for the grantee (Ignite Reading) that relied on DIBELS as the outcome measure.

Figure 1: Tutoring Efficiency Metric, by Growth Benchmark



Notes: Figure shows Tutoring Efficiency, which is defined as the number of hours of tutoring to improve student learning by one month, for two types of student growth benchmarks: (i) test-specific, which is the estimated average annual growth in student learning (by grade-level and subject area) based on the study's test-specific outcome measure; and (ii) Hill et al. (2008), which is the estimated average annual growth in student learning (by grade-level and subject area) from Hill et al. (2008), which relies on a composite measure of expected student growth from multiple nationally-normed assessments of student achievement. The calculation of provider-specific Tutoring Efficiency relies on the actual (mean) dosage received during the study period. Based on evidence of tutoring program impacts from prior experimental evaluations reported in Kohlmoos & Steinberg (2024), mean Tutoring Efficiency for literacy tutoring interventions was 39.6 hours (standard deviation=25.3); for math tutoring interventions, mean Tutoring Efficiency was 13.7 hours (standard deviation=6.9).

[2] To calculate Tutoring Efficiency, we first normalize the program-by-outcome effect (Effect Size) by grade-level and subject area because relative gains in student achievement vary by grade and subject. This normalization is necessary because, for example, an effect size of 0.15 SD represents a larger gain in student learning for students in grade 6 than for students in grade 1 because the average annual growth in student achievement (in standard deviation units) is greater for lower grades than for upper grades. To normalize a standardized effect size, we must rely on a growth benchmark, or the average annual growth in student achievement (in SD units) at the grade and subject levels. By dividing the program-by-outcome effect size by a growth benchmark, we generate the percent of average annual growth in student achievement generated by a specific tutoring program. The percent of average annual growth in student achievement is then used to calculate the number of additional months of student learning (at the grade- and subject-level) generated by the program.

Estimates of Tutoring Efficiency from Figure 1 rely on the average treatment effect of the program (i.e., intent-to-treat effect). Yet, there is likely variability in Tutoring Efficiency as a function of both the magnitude of the average treatment effect and the precision of the average treatment effect due to sampling variability (i.e., study sample size). Figure 2 presents the variability in the Tutoring Efficiency metric for the four tutoring program providers by showing lower and upper bound estimates (based on the 95% confidence interval of the program impact estimate).[3] Estimated bounds around the Tutoring Efficiency metric provide decisionmakers with a range of time (i.e., hours of tutoring dosage) within which a program might be expected to improve student learning. First, we show that variability in Tutoring Efficiency reflects uncertainty in the average treatment effect due to study sample size and the magnitude of the average treatment effect. Second, as the average treatment effect (in SD units) goes to zero, the interpretation of the Tutoring Efficiency metric becomes less useful since a very small impact estimate will lead to a very large value of Tutoring Efficiency.[4] These findings suggest the need for larger study samples to produce more efficient and precise estimates of Tutoring Efficiency (we note that Accelerate's newest grant program, Evidence for Impact (EFI), requires larger sample sizes to approximate scale as part of the 2025-26 school year RCTs) and the importance of designing evaluation studies to detect effects of a reasonable magnitude (e.g., 0.10-0.15 SDs). We remind readers that estimates of Tutoring Efficiency are relevant for program providers with statistically significant estimates of program impact.

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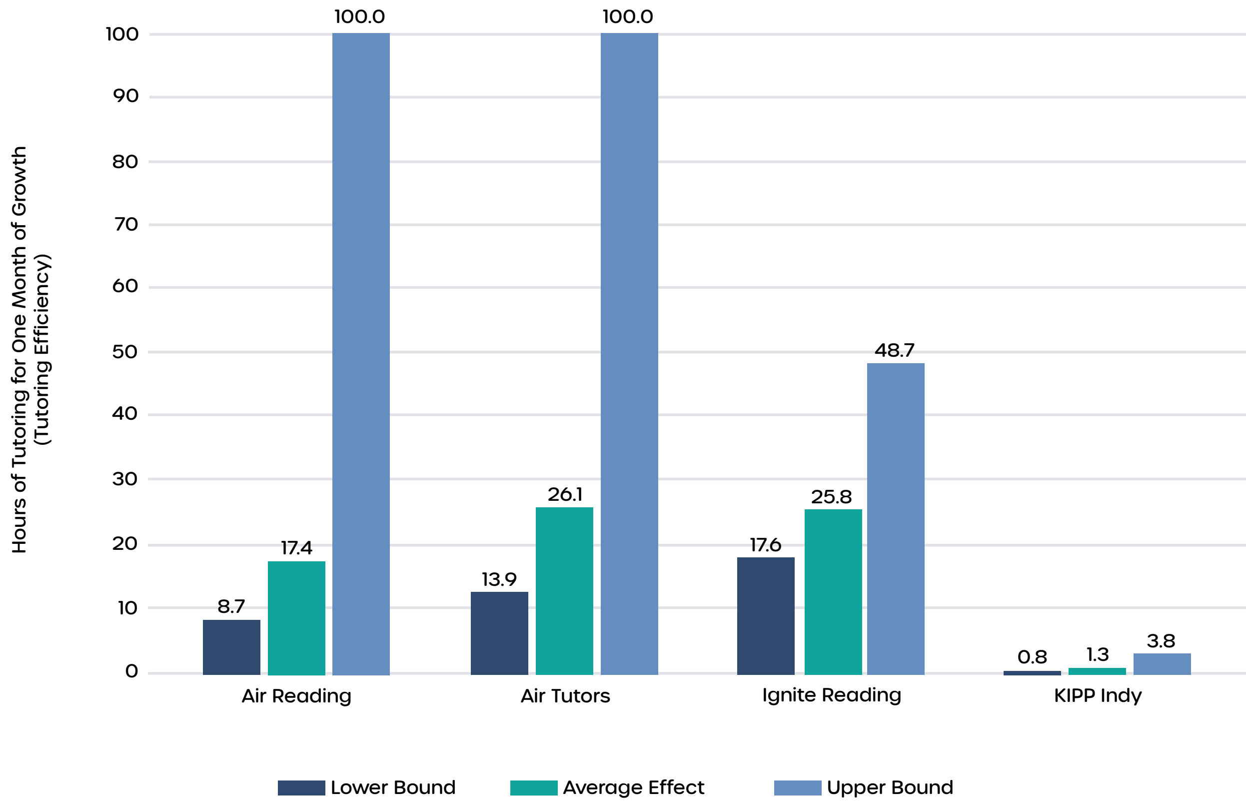
[3] We construct the lower and upper bound estimates of Tutoring Efficiency by first calculating the 95% confidence interval of the average treatment effect (in standard deviation units). We then calculate the Tutoring Efficiency metric for the lower and upper bound estimates of the 95% confidence interval by translating the standardized units to months of additional learning based on the Hill et al. (2008) summative benchmark for average annual growth in student achievement. We then use actual dosage received during the program implementation to calculate the upper and lower bound estimates of the Tutoring Efficiency metric.

[4] As the average treatment effect (in SD units) of the program goes to zero, a very small impact estimate will lead to a very large value of Tutoring Efficiency (ultimately approaching infinity). The upper and lower bounds of the Tutoring Efficiency metric provide empirical insight into the potential variability in the efficiency of a tutoring program for a given program implementation. The upper bound estimates of Tutoring Efficiency for Air Reading and Air Tutors are very inefficient (in terms of the return on tutoring dosage) and have been censored at 100.

Figure 2: Variability of Tutoring Efficiency Metric



Notes: Figure shows the upper and lower bounds of Tutoring Efficiency, which is defined as the number of hours of tutoring to improve student learning by one month, along with the average effect (from Figure 1). To construct the lower and upper bound estimates of Tutoring Efficiency, we first calculate the 95% confidence interval of the average treatment effect (in standard deviation units). We then calculate the Tutoring Efficiency metric for the lower and upper bound estimates of the 95% confidence interval by translating the standardized units to months of additional learning based on the Hill et al. (2008) summative benchmark for average annual growth in student achievement. We then use actual dosage received during the program implementation to calculate the upper and lower bound estimates of the Tutoring Efficiency metric. The upper bound estimate of Tutoring Efficiency for Air Reading and Air Tutors have been censored at 100.

We conclude by posing some outstanding questions about the validity, precision, and comparability of the Tutoring Efficiency metric that remain to be pursued. First, the research designs varied even among this small sample of tutoring providers. Thus, it will be important to generate larger samples of program impact estimates based on common research designs (e.g., RCTs) to improve the comparability of Tutoring Efficiency estimates. Second, to what extent does Tutoring Efficiency vary across implementation settings within tutoring providers? To address this question, the field will require significantly more replication studies based on the same research design to generate a within-provider distribution of Tutoring Efficiency to better understand how (and to what extent) Tutoring Efficiency might differ for the same provider in different school and district settings. Third, to what extent does variation in Tutoring Efficiency reflect differences in the duration of tutoring (e.g., 1 semester versus full year) and the timing of tutoring (e.g., spring versus fall semester)? And further, does variation in Tutoring Efficiency reflect the timing (e.g., middle-of-year versus end-of-year assessments) and scope (e.g., diagnostic assessments; nationally normed assessments; state-specific assessments) of the outcome measure? As Accelerate continues to develop the evidence base on tutoring program impact and Tutoring Efficiency through our grantmaking efforts, we aim to address these and other outstanding questions to continue to inform the field on the expected return on the time necessary to improve student learning.

Part Two

Research Roundup

In this Research Roundup, we describe new findings on the implementation and impact of high-dosage tutoring during the 2023-24 school year from the Personalized Learning Initiative (PLI) and summarize and present new evidence on the growing promise of virtual tutoring.

Personalized Learning Initiative: Preliminary Findings from the 2023-24 School Year

In QRN 1.2, we first profiled results from the 2022-23 school year of the Personalized Learning Initiative (PLI), a multi-year, multi-site experimental evaluation of tutoring to understand what models of tutoring work best for which students in which contexts, and at the lowest possible cost. Results from the 2022-23 school year were among the first indications that in-school high-dosage tutoring, done at scale, can effectively counteract pandemic-era learning setbacks.

In June 2025, the University of Chicago Education Lab and MDRC released preliminary results from the 2023-24 school year of the Personalized Learning Initiative (PLI). The data provides impact findings from over 17,000 students who were randomly assigned to receive tutoring during the 2023-24 school year across eight partner sites nationwide. Most site partners offered both a more resource intensive type of high-dosage tutoring (HDT), as well as a less resource intensive tutoring intervention that the PLI calls sustainable high-dosage tutoring (SHDT). Tutoring typically supported either early grade (K-5) literacy or middle school (6-8) math.

The PLI research team have found positive and statistically significant effects, for both higher cost, HDT models (approximately $2,000 per student) and lower cost, SHDT models (approximately $1,200 per student). Tutoring impacts are robust across a variety of different models; for example, virtual tutoring seems to be just as effective as in-person tutoring.

STUDY SNAPSHOT | Personalized Learning Initiative (PLI)

PUBLISHED: June 2025
RESEARCH TEAM: University of Chicago Education Lab and MDRC
STUDY PERIOD: 2023-24 school year
RESEARCH METHOD: Randomized Controlled Trial (RCT)

STUDENT GROUP(S) STUDIED: Over 17,000 grade K-12 students enrolled in the study across eight site partners nationwide, including: Chicago Public Schools (IL); Winston-Salem/Forsyth County Schools (NC); Guilford County Schools (NC); Greenville County Schools (SC); Miami-Dade Public Schools (FL); Fulton County Schools (GA); New Mexico Public Education Department (NM); and Rocketship Charter Schools (CA).

STUDY QUESTIONS:
- What is the impact of higher and lower cost tutoring models on student achievement?

KEY FINDINGS:
- Tutoring is effective overall in improving student learning, though there is considerable variability across sites.
- Tutoring impacts seem robust across a variety of models.
- Lower cost models ($1200 per student) are just as effective as higher cost models ($2000 per student).
- Virtual tutoring seems just as effective as in person tutoring in PLI sites.
- More tutoring dosage correlates with greater learning gains.
- Tutoring dosage was much lower than past tutoring studies (corresponding to smaller gains in student learning).

KEY TAKEAWAYS:
- Results provide additional evidence on the promise of virtual tutoring, showing that small group virtual tutoring can significantly improve student math achievement.
- Ensuring that students receive adequate levels of tutoring dosage is necessary for driving improvements in student achievement.

*Note: These are preliminary results and are subject to change. For more information on the PLI study, contact Monica Bhatt, Senior Research Director of the University of Chicago Education Lab.

When the PLI research team examines student learning gains relative to the amount of tutoring dosage that students received, evidence indicates that there is a positive trend line across PLI partners for both HDT and SHDT. That is, more tutoring dosage correlates with greater student learning gains. However, the amount of tutoring students received during the 2023-24 school year fell far below the amount of tutoring received in prior pre-pandemic studies of tutoring. In the PLI's pre-pandemic benchmark, students received 33-82 hours of tutoring per year; in contrast, in all but one PLI site, students received 20 or fewer hours of HDT or SHDT. The exception was New Mexico, where dosage and impacts were among the strongest of all site partners, with an average of 38 hours of HDT received over the year and impacts of 0.12 standard deviations (based on the PLI's intent-to-treat impact analysis). While more tutoring dosage correlates with greater learning gains, the amount of tutoring delivered during the 2023-24 study was lower than past tutoring studies, corresponding to smaller gains in student learning. These preliminary findings should encourage the field to stay the course in focusing on how to improve implementation of high dosage tutoring in order to maximize tutoring dosage to yield greater learning gains for students.

In addition to the impact analyses, the PLI study also incorporates implementation and cost study components, including surveys which ask tutors and school coordinators about their experiences implementing tutoring. This data will help districts understand the costs of various tutoring program designs, including best practices for tutoring implementation. In addition, the PLI team has developed site-specific case studies (such as this example from New Mexico) that help tell the story of how tutoring has unfolded and evolved over time in each site. The ultimate goal of the PLI is to understand not just whether local adaptations of tutoring work on average, but to understand which adaptations work, for which students, and in which contexts. The PLI research team looks forward to sharing additional results in the coming years.

The Growing Promise of Virtual Tutoring

In QRN 1.1 and QRN 1.3, we have described and highlighted the promise of virtual tutoring for improving student learning outcomes. We have shown that individualized (i.e., 1:1 tutor-student ratio) online tutoring in early literacy for grades K-2 students improved reading achievement by 0.11 SD, an additional 1-1.5 months of learning (see QRN 1.1). We have also documented how live virtual instruction in groups of 3 (i.e., 1:3 tutor-student ratio) for students in grades 1-6 improved the reading achievement of tutored students by 0.12 SD, corresponding to 1.6 additional months of learning (see QRN 1.3). Notably, students who received at least 40 tutoring sessions (the intended dosage) realized significantly larger gains of 0.17 SD, or approximately 2 additional months of learning in reading achievement versus treated students who received fewer than 40 total sessions, a result consistent with evidence from the 2023-24 PLI results showing that greater tutoring dosage is associated with greater student learning gains.

Results from PLI during the 2023-24 school year also provide further evidence on the promise of virtual tutoring. The PLI partnered with Greenville County Schools (SC) to conduct a three-arm RCT to study the impact of virtual tutoring and the impact of an EdTech intervention (both compared to a business-as-usual control condition). Approximately 2,000 students (across three schools) in grades 6-8 were randomly assigned to either live virtual tutoring (from Littera Education) in groups of 3 (i.e., 1:3 tutor-student ratio); a personalized edtech product that offered individualized content and practice opportunities; or the business-as-usual condition. Both the virtual tutoring and edtech intervention had intended dosage of three sessions per week for 30 minutes per session over the course of a 20-week period.

On average, students randomly assigned to the virtual tutoring intervention and the edtech intervention received approximately 20 sessions of the intervention over the course of the 2023-24 school year. Yet, students randomly assigned to virtual tutoring realized significant improvements in math achievement, on the order of 0.10 SD, corresponding to approximately 3 additional months of learning for middle-grade students (approximately one-third of the math an average middle school student learns in an academic year). Students randomly assigned to the edtech intervention did not realize any additional impact on their math achievement compared to students randomly assigned to the business-as-usual condition. This PLI result adds to a growing body of evidence that virtual tutoring increasingly shows promise in addressing pandemic learning loss in a cost-effective way (see "[Can Virtual Tutoring Address Pandemic Learning Loss in a Cost-Effective Way](#)").

STUDY SNAPSHOT | Littera

PUBLISHED: June 2025
RESEARCH TEAM: University of Chicago Education Lab and MDRC
STUDY PERIOD: 2023-24 school year
RESEARCH METHOD: Randomized Controlled Trial (RCT)

STUDENT GROUP(S) STUDIED: In Greenville County Schools (SC), all middle school students (grades 6-8) at three schools (approximately 2,000 students) were eligible to be randomized to one of two interventions: virtual tutoring (via Littera); edtech; or business-as-usual (BAU).

STUDY QUESTIONS:

- What is the impact of high-dosage tutoring (HDT) via live virtual instruction on middle school math achievement?
- What is the impact of sustainable high-dosage tutoring (SHDT) via an edtech intervention on middle school math achievement?

KEY FINDINGS:

- Students randomly assigned to the virtual tutoring intervention (Littera) and the edtech intervention received approximately 20 sessions of the intervention (out of a total intended dosage of 60 sessions) over the course of the 2023-24 school year.
- Students randomly assigned to virtual tutoring realized significant improvements in math achievement, on the order of 0.10 standard deviations (SD).
- Students randomly assigned to the edtech intervention did not realize any impact on math achievement compared to students in the BAU control condition.

KEY TAKEAWAYS:

- Results provide additional evidence on the promise of virtual tutoring, showing that small group virtual tutoring can significantly improve student math achievement.

*Note: These are preliminary results and are subject to change. For more information on the PLI study, contact Monica Bhatt, Senior Research Director of the University of Chicago Education Lab.

Part Three

Looking Ahead

Since the 2022-23 school year, Accelerate has supported research studies of more than 100 tutoring providers. In the 2024-25 school year alone, Accelerate has sponsored 28 research studies, including 15 randomized controlled trials (RCTs), 7 quasi-experimental evaluations, and 6 implementation studies. Together, these studies have revealed new insights and generated novel evidence on the design, implementation, and impact of tutoring. For example, we have shown the promise of virtual tutoring models - such as OnYourMark and Air Reading - for remediating pandemic learning loss (see QRN 1.1; QRN 1.3); the potential of targeted early literacy instruction - via a small-scale RCT of Reading Futures - for supporting students with dyslexia (see QRN 1.4); and the impact of program design features such as group size (i.e., tutor-student ratio) and session frequency via multi-arm RCTs of OnYourMark and KIPP Indy (see QRN 1.1; QRN 1.3).

Accelerate's research portfolio has also revealed important known unknowns, including the need for more research into the specific tutoring programs that improve student learning, for which students, in what educational contexts, at what costs, and the program design features most associated with student achievement gains. Filling these evidence gaps is the impetus behind one of Accelerate's newest grant programs to be launched during the 2025-26 school year: Evidence for Impact (EFI).

The EFI grant program will focus exclusively on RCTs that are well-designed and well-powered and which fill specific evidence gaps. EFI RCTs will prioritize multi-arm trials that test the impact of specific tutoring program design features, including group size, tutor type, and modality, and will do so by relying on sample sizes that aim to approximate the impact of tutoring providers at scale. EFI research studies will focus on building evidence to better understand the impact of tutoring for understudied student groups, including students in secondary grade levels (grades 6-12) and understudied content areas (such as math), and for students with individualized education plans (IEPs), multilingual learners, and economically disadvantaged students. EFI evaluations will focus on policy-relevant outcomes, such as end-of-year state exams and nationally norm-referenced assessments. Each RCT will incorporate a rigorous cost analysis - leveraging Accelerate's cost analysis tool - to measure a program's cost of implementation and to pair program cost with an experimental estimate of program impact to calculate program-specific cost-effectiveness. EFI RCTs will also implement a teacher-level survey to empirically measure the business-as-usual condition (for control group students) to more precisely quantify and contextualize the treatment/control contrast.

Artificial Intelligence (AI) and technology-enabled learning and instructional tools are rapidly entering classrooms, but evidence about their effectiveness remains limited. As educational technology companies launch new products, educators and leaders must make decisions without sufficient data on which tools improve learning outcomes across diverse student populations and whether their benefits justify implementation costs. During the 2025-26 school year, the second of Accelerate's newest grant programs - Call for Effective Technology (CET) - aims to address the existing gaps in the research by funding promising AI and tech-enabled tools and studying their program design, usability, implementation, impact, and cost-effectiveness. CET research studies will also support comparative analyses, providing important new insights into the design of and engagement with fully AI-enabled vs. AI-enhanced vs. human-only tutoring models, and whether AI tools can address some of the common implementation and scaling barriers present in human-powered tutoring programs.

Accelerate will continue to partner with our robust network of research organizations via the Research Learning Community to develop, design, and implement evaluations of EFI and CET grantees during the 2025-26 school year. Please see Accelerate's Research Agenda and Call for Effective Technology (CET) Research Learning Agenda, which describe in greater detail the full scope of what Accelerate aims to learn through the EFI and CET research studies on the design, implementation, impact, and cost-effectiveness of tutoring and personalized learning interventions.

We welcome readers to share with Accelerate research studies that examine the design, implementation, and/or impact of tutoring programs and personalized learning initiatives. Please contact Matthew Steinberg, Accelerate's Managing Director of Research and Evaluation, with any research studies you wish to share for potential inclusion in a future issue of the Quarterly Research Note.

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