Evaluating a Personalized Online Learning Tool for Academic Recovery: Lessons from i-Ready

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Abstract
Many K–12 school districts are leveraging online personalized learning platforms as part of their COVID-19 recovery efforts. We examined the extent to which one such platform, i-Ready, was associated with improved student achievement growth in a southeastern district. We find that students performed better on math and reading standardized assessments when using i-Ready; this is especially true for students who received FRPM, identified as Black, and/or identified as male. Additionally, students whose teachers assigned at least one lesson in addition to automatically assigned lessons benefited even more from i-Ready use. Consistent with prior research, online instructional tools appear most effective when used 40 to 100 hours a school year, with diminishing returns past that point. Our findings suggest that when implemented in a manner that integrates teacher expertise and at an appropriate dosage, platforms such as i-Ready are useful recovery tools that can help school districts enhance student learning, particularly for students belonging to marginalized groups. Further, online learning tools may be particularly beneficial in instances where high cost, low uptake, and/or participant stigma might limit the effectiveness of more traditional remediation strategies.

Keywords: Adaptive learning; blended learning; personalized learning; COVID-19 pandemic recovery; K–12 education policy; quasi-experimental design

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The COVID-19 pandemic resulted in widespread school closures beginning in March 2020 (Goldstein et al., 2020). To maintain schooling during this period, the majority of schools transitioned to crisis-driven virtual learning that continued for many well into the 2020-21 school year (Kaufman & Diliberti, 2021). During this time, students experienced drastic reductions in academic growth compared to pre-COVID-19 cohorts (Darling-Aduana et al., 2022; Kogan & Lavertu, 2021; Kuhfeld & Lewis, 2022; Kuhfeld et al., 2022; Patrick et al., 2021; Pier et al., 2021; Renaissance Learning, 2021). Since then and despite substantial investments in recovery interventions, students have experienced inconsistent academic recovery (Carbonari et al., 2022; Lewis & Kuhfeld, 2023; Curriculum Associates, 2023). Given the challenges to academic recovery, states and school districts continue to seek ways to improve student performance.

Among a host of strategies, many K–12 districts have turned to online tools to assist in student learning recovery. The rapid switch to virtual learning during COVID-19 precipitated large-scale investments in virtual learning infrastructure, programs, and professional development. These investments changed the landscape of how and in what way virtual learning will play a role in students' educational experiences moving forward. As such, our research seeks to assess the effect of one virtual learning strategy—the widely used i-Ready Personalized Instruction platform—on student achievement and recovery.

We studied i-Ready because it was the online learning platform used by the K–12 school district in which we are engaged in a multi-year Research Practice Partnership. As part of their COVID-19 recovery strategy, the school district made i-Ready available to schools. Teachers had discretion over use but were encouraged to assign regular lessons and activities within the platform. Students could access and complete i-Ready activities both during and outside of the school day. i-Ready has several key features typical of online learning platforms, including diagnostic testing, computer adaptive assessment, personalized instruction, and responsive instruction that adjusts pacing based on student understanding. In studying i-Ready, we aim to speak to the potential of the wider array of online learning platforms with similar features.

Studies examining the role of online learning platforms in students' post-pandemic recovery are nearly non-existent. This study is the first that centers solely on online instructional tools. The only other study we are aware of that estimated effect sizes of online learning platforms as a COVID-19 recovery intervention examined them as one of many interventions (Carbonari et al., 2022). As such, researchers were unable to examine the specific features and usage of the various platforms identified. Our study also provides one of the first investigations of online personalized learning platform at-scale. Despite these platforms becoming an increasingly common instructional tool in the post-pandemic education landscape, a recent meta-analysis on the topic failed to identify studies of interventions serving more than 300 students (Zheng et al., 2022).

To extend knowledge in this area, we examined the associations between student achievement growth and i-Ready usage overall, by feature, and for students across various prior performance levels, grades, and sociodemographic variables. We conducted this analysis using data from a K–12 metro district in the southeast. More specifically, we leveraged the staggered rollout of i-Ready in the district as well as detailed administrative and log data from the online

instructional platform. In doing so, this study aims to expand understanding of online interventions and contribute to research on the post-COVID-19 learning landscape.

The Post-Pandemic Education Landscape

Early studies of students' COVID-19 achievement recovery found that the pandemic's negative effect on student achievement grew during the 2020–21 school year (Sass & Goldring, 2021; Kuhfeld et al., 2022). By fall 2021, students began to recover slightly, with students' pace of achievement progress matching or approaching pre-pandemic norms (Kuhfeld & Lewis, 2022; Sass & Goldring, 2022). Fahle et al. (2024) found that students recovered a third of their original loss in math and a quarter of their loss in reading between spring 2022 and spring 2023, reflecting larger than typical growth. Students also achieved improvements in math proficiency on state assessments in most states between 2021 and 2023; however, there is less evidence of recovery in reading (Barnum & Belsha, 2023; Oster, 2023). Despite progress, most students continued to perform below their pre-pandemic national percentile ranking (Carbonari et al., 2022; Curriculum Associates, 2023; Fahle et al., 2024; Sass & Ali, 2022). Kuhfeld and Lewis (2022) estimate that students would need a minimum of three school years to fully recover academically.

COVID-19 Recovery Interventions

Since the pandemic, school districts have offered four main interventions to promote student academic recovery: extended school calendars, tutoring, after-school or out-of-school-time programs, and online instructional tools. Each intervention aims to provide additional instructional and learning time to students beyond the traditional school day. We discuss the implementation and general successes of each in turn.

Extended School Calendars and Days

To offer students additional days of instruction for recovery, some school districts extended their school year (Carbonari et al., 2022). Some districts began the school term early day (Kraft & Novicoff, 2022; Carbonari et al., 2022). Others integrated additional school days or optional days for extra support or teacher professional development, and a third group extended the school day (Kraft & Novicoff, 2022; Carbonari et al., 2022). Pre-pandemic research points to generally positive increases in achievement when students have at least ten more days added to their school calendar (Aucejo & Romano, 2016; Kraft & Novicoff, 2022) or when extending the school day (Kraft & Novicoff, 2022; Figlio et al., 2018; but see Checkoway et al., 2013). Despite this circumstantial pre-pandemic evidence, researchers studying the implementation of extended school time post-pandemic failed to identify positive impacts (Carbonari et al., 2022).

Tutoring

Pre-pandemic research also demonstrates that high-dosage tutoring (of at least 30 minutes daily tutoring outside the school day) can significantly improve student learning in math and reading (Allensworth & Schwartz, 2020; Hashim et al., 2024; Markovitz et al., 2022). Models varied in hours of tutoring (e.g., 30-minute or 90-minute sessions), frequency (e.g., daily or four days a week), and format (e.g., one-on-one tutoring or small group tutoring sessions), yielding

varying levels of effectiveness in student recovery (Allensworth & Schwartz, 2020; Hashim et al., 2024). Districts that offered fewer hours of tutoring experienced limited effects on student recovery, while districts that engaged in more frequent, targeted high-dosage tutoring, traditionally defined as 50 hours or more of tutoring over 36 weeks (see Fryer, 2016), experienced meaningful progress toward recovery (Carbonari et al., 2022).

After-school and Out-of-school Programs

Extended instructional time interventions were also used for pandemic recovery. Strategies to extend instruction time include extended summer school, before-school, after-school, and out-of-school programs. In contrast to extended calendar or school-day interventions, these programs typically offer a combination of academic and enrichment activities, in which students may receive additional instructional time in small groups rather than individualized, high-dosage assistance (Gershenson & Lomax, 2021; Carbonari et al., 2022). These programs tend to target lower-performing students. Pre-pandemic findings suggest that six weeks of summer learning can produce up to a quarter of a year of learning (Augustine et al., 2016). However, the effects of pandemic recovery summer school are minimal, with the most positive study identifying that summer school could close only 2 to 3 percent of a district's total learning losses in math (Callen et al., 2023; Carbonari et al., 2022).

Virtual Learning and Online Instructional Tools

Lastly, districts turned to online instructional tools to aid in student recovery. i-Ready (discussed in more detail below) stands among a host of these platforms (e.g., ALEKS, Dreambox). Some districts rely on online instructional tools during core instruction, while others use them to extend or add instructional time to core instruction (Carbonari et al., 2022). Research on online tool effectiveness as a pandemic recovery strategy is limited. However, Carbonari and colleagues (2022) find marginal effects for this intervention in one district.

Conditional on effectiveness, virtual platforms do not face many of the challenges of other recovery interventions, such as stigma, low uptake, and requiring real-time (synchronous) instructor support. Family and student uptake of educational recovery interventions has been low when delivered as optional programs (Carbonari et al., 2022; Kraft & Falken, 2021; Silver et al., 2022), whereas virtual platforms can be integrated during the school day or assigned as homework. Participation does not require transportation or changes to family schedules. Students can access the program anytime, anywhere using a web browser and their login credentials. Additionally, when integrated within the regular school day, the use of online tools can provide instructional activities for students, allowing teachers to reallocate their attention to higher-impact learning tasks, including providing support for students who require the most remediation (Darling-Aduana & Heinrich, 2018). Lastly, there is some concern that uptake of remediation interventions might be depressed due to concerns over stigma (Kraft & Falken, 2021; Nickow et al., 2024), which is less likely to occur when programs are offered universally. The current study adds to the small, growing body of research on the effectiveness of online tools as a recovery strategy.

Online Instructional Tool Features

According to their website, i-Ready is a suite of online instructional tools that includes assessment, screening, and math and reading lessons. K–8 standards-aligned formative assessments and adaptive assessments provide feedback on specific content students need help mastering. There are also specialized tools designed for students receiving special education services and for students enrolled in pre-kindergarten and Head Start programs. i-Ready marketing materials describe its system as providing "explicit and systematic instruction" within lessons that are "active, supportive, and relevant to their lives" (i-Ready, 2025). Lessons emphasize active strategies like polling, experimentation, learning games, and working with manipulatives (i.e., objects like blocks, dice, and dominoes that can be used to make math more concrete; Carbonneau et al., 2013). Many lessons are also responsive, which i-Ready defines as adjusting the pace of the lesson to how quickly the learner is mastering content. Assessment data is used to direct students to K–8 reading and math lessons covering content they have yet to master. Alternatively, or in addition, teachers can select (or deselect) lessons for their students to complete. Lessons are available in both English and Spanish with features designed to support English language learners. As such, i-Ready combines several features available across online learning tools designed to be blended into traditional in-person instruction, including: vendor-developed, asynchronous content delivery, adaptive online diagnostic assessment, and personalized learning.

Prior research has documented that asynchronous lessons developed by the largest online course vendors tend to focus on lower-order cognitive tasks due to the emphasis on creating highly standardized, structured lessons that can be mass-produced and implemented with minimal instructor oversight (Darling-Aduana, 2021; Darling-Aduana & Hemingway, 2022). Assessments tend to be predominantly multiple-choice questions that only require students to remember and recite instead of thinking critically about content (Darling-Aduana, 2021; Darling-Aduana et al., 2024). In other words, few of these technology-facilitated programs facilitate the type of authentic tasks and interactions that support meaningful online learning (Woo & Reeves, 2008). Additionally, answers to assessments designed by many of the largest online course vendors are readily available online, with frequent evidence of cheating (Heinrich et al., 2019; Darling-Aduana et al., 2024). Consequently, student outcomes tend to be negative, especially for students with lower prior achievement levels or less ability to self-regulate (Heinrich et al., 2019; Ahn & McEachin, 2017; Besecker et al., 2020; Fitzpatrick et al., 2020; Gonzales et al., 2020; Woodworth et al., 2015).

However, instructional quality and subsequent outcomes may be more positive when content is developed by smaller-scale, research-based vendors and/or is targeted toward specific skills (Sahni et al., 2021; Wijekumar et al., 2014, 2017). As an example, Cambolat and Arndt (2024) identified positive learning associations of 0.14 standard deviations among students using Lexia PowerUp, which focuses solely on word recognition for middle and high school students. Students also appear to benefit more from asynchronous, online instruction when blended with traditional, face-to-face instruction instead of as a stand-alone intervention (Heppen et al., 2011; Wiburg et al., 2016).

Beyond delivering course content, one commonly cited but rarely fully realized opportunity to leverage the strengths of technology involves providing students with a personalized learning experience (Enyedy, 2014). The most common digital systems, strategies,

and/or tools used to facilitate personalized learning include adaptive learning or tutoring systems, computer games, robotics, virtual reality, and learner preference-based personalization (Zheng et al., 2022). A meta-analysis identified a moderate association between the use of these technology-facilitated personalized learning tools and student achievement with personalized diagnosis and guidance associated with the highest rate of achievement (Zheng et al., 2022). Studies of ISI-Math and ITSS programs with adaptive learning similar to i-Ready have found positive associations with student test scores (Connor et al., 2018; Wijekumar et al., 2014, 2017).

Prior research on the use of online instructional materials also identified the importance of dosage (i.e., the frequency, number of times, or total time students interact with the tool) (Darling-Aduana & Heinrich, 2018, 2019a; Cambolat & Arndt, 2024; Heinrich et al., 2014). When examining the use of digital tools for out-of-school tutoring across several large metro districts, researchers identified 40 hours of tutoring per school year as a critical threshold for observing positive associations (Heinrich et al., 2014). Similarly, a study examining the use of a computer-assisted literacy program found an hour of use a week (or around 36 hours a year) was necessary for improved test scores (Cambolat & Arndt, 2024).

Importantly, prior research has established that certain students are more likely to benefit from (or struggle with) online learning. Students belonging to advantaged groups, including students with access to technology and internet at home and with higher prior achievement levels, are more likely to be successful learning online (Heinrich et al., 2019; Munoz-Najar et al., 2021; Warschauer & Matuchniak, 2010; Wijekumar et al., 2014). Further, most online learning tools place increased responsibility on students to manage their own learning (Jacob et al., 2016). Consequently, students with stronger self-regulation skills (including older students) or greater parental or teacher-provided monitoring and support are more likely to benefit from online instruction (Darling-Aduana, 2021; Darling-Aduana et al., 2019; Borup et al., 2019; Liao et al., 2021; Picciano & Seaman, 2007).

Additionally, students interact with and experience online learning tools differently based on their sociodemographic background and identities. Several prior studies have found higher rates of engagement with online learning platforms and subsequent achievement among female (versus male) high school students (Darling-Aduana et al., 2022; Lowes et al., 2016; Mann et al., 2021). Students receiving FRPM and from historically marginalized racial groups were notably less likely to achieve expected learning gains when learning online (versus face-to-face) during the pandemic (Darling-Aduana et al., 2022; Mann et al., 2021). It is, of course, possible, given the differential effects of the pandemic, that these associations may be due to confounding factors. In contrast, a recent meta-analysis of 36 studies found that English language learners experienced moderate gains in literacy (ES = 0.47) when taught in technology-integrated versus fully face-to-face classrooms (Lee et al., 2022; see also Darling-Aduana & Heinrich, 2018; Cambolat & Arndt, 2024). Results from students receiving special education services who are learning via technology show positive, null, and negative associations with learning observed across three different blended learning environments (Basham et al., 2016; Pace & Mellard, 2016).

Further complicating the matter, the above studies examine a range of online learning contexts, including fully online courses and technology-integrated, traditional (i.e., blended)

classroom environments. Research on adaptive learning programs, like i-Ready, is more limited. One prior study of i-Ready, reviewed by the What Works Clearinghouse, identified positive associations with achievement (Randel et al., 2020). The study was rated Meets WWC Standards with Reservations due to the use of a quasi-experimental (versus experimental) research design (WWC, 2024). i-Ready received a rating of Partially Convincing Evidence on the Academic Intervention Tools Chart (2025) for the same 2020 study by Randel and colleagues. Similarly, Evidence for ESSA awarded i-Ready a Moderate rating based on a single quasi-experimental study that identified positive associations with test scores (Evidence for ESSA, 2025; Holzman & Duncan, 2022). All of the reports reviewed for these ratings were conducted by or on behalf of Curriculum Associates, the vendor that sells i-Ready. Common Sense, a non-profit funded by corporate and foundation sources, also offers generally positive reviews of the tool as a test-prep solution but cautions that it is not a replacement for classroom teaching and that activities follow a similar format that can become repetitive (Common Sense, 2025). Educators have also raised concerns regarding recommendations by the publisher and, in some states, to use i-Ready as much as 90 minutes a week, particularly if i-Ready is used in place of in-person instructional experiences (Gates, 2024; McKinnon, 2018).

When reviewing studies using adaptive learning programs similar to i-Ready, we identified one study that observed positive math test score gains among second-grade students, appearing consistent across poverty level, gender, and prior math test scores (Connor et al., 2018), while Wijekumar and colleagues (2014) found that students with high prior achievement obtained higher gains when using an adaptive, technology-based literacy tool. Perhaps most importantly, the previous findings on online learning have largely been obtained in the context of a "normal" academic year in which students and teachers are not faced with extenuating circumstances that could also influence outcomes. The research on academic recovery is growing; however, most studies do not focus exclusively on the role of technology in meeting recovery goals. Instead, scholars have centered recovery research around tutoring and extended time programs.

Accordingly, this study extends existing research on the efficacy of COVID-19 recovery interventions to online instructional materials by examining the following research questions: (1) To what extent was student use of online instructional materials associated with improved student achievement growth in the post-pandemic era? (2) By how much did student achievement growth vary by i-Ready usage and whether the teacher or automated system assigned instructional materials? (3) To what extent did students experience differential rates of student achievement growth associated with i-Ready usage by prior performance level, grade level, and sociodemographic variables (i.e., gender and race/ethnicity as well as English learner (EL), free and reduced-price meals (FRPM) eligibility, identified disability, and disciplinary status? We detail the setting, sample, data, and analytic strategy employed to answer these research questions in the following section.

Methods

Setting, Sample, and Data

We partnered with a school district in a southeastern metro area that uses the i-Ready Personalized Instruction platform as a COVID-19 recovery strategy. In addition to use during the school day, students could access the platform anytime, anywhere using a web browser and their login credentials. Our research partner is a one-to-one district that provides Chromebooks to all students, with grant funding used to provide internet hotspots to students without internet access. To support this study, the district partner provided access to student-level administrative and log data on i-Ready usage and scores, demographics, summative assessment test scores, and school characteristics.

The i-Ready platform provides interactive lessons and nationally normed adaptive formative assessments. Additionally, the district conducts fall, winter, and spring Measures of Academic Progress (MAP) assessments, allowing for the estimation of achievement growth at the semester level. MAP is a computer-adaptive standardized assessment used by over 16 million students across over 50 thousand schools (NWEA, 2015). We report MAP test scores as z-scores, which we calculated by standardizing scale scores by grade and subject, so that the mean of each test score (by grade and subject) is zero with a standard deviation of one. Standardizing the variables in this manner allowed us to compare across grades and subjects. Z-scores were calculated based on the national distribution of pre-pandemic scale scores.

Of the 131 schools in the district, 81 used i-Ready during SY 2021–22 (Year 1). Eighty-four schools used i-Ready during SY 2022–23 (Year 2). The district prioritized providing low-performing schools access to i-Ready. In Year 1, schools that were currently or previously identified as Comprehensive Support and Improvement (CSI) (n = 35) were more likely to use i-Ready than non-CSI schools (67% versus 57%). CSI schools are an official Every Student Succeeds Act (ESSA) distinction assigned to schools requiring additional support. Schools are assigned CSI status if they are in the lowest performing 5% of schools in the state or if a high school's four-year graduation rate is under 68% in a given year. "Horizon school" is a district-assigned status that aligns loosely, but not perfectly, with CSI status. For this analysis, we included binary variables for both whether a school was ever designated as CSI status and whether a school was ever designated as Horizon status as signs of priority status for i-Ready usage. Thirty-three to thirty-five percent of students attending priority schools used i-Ready compared to 14% of students who did not attend a priority school.

Consistent with the focus on providing priority schools with earlier access to i-Ready, a significantly higher percentage of i-Ready users received FRPM (67%) than non-i-Ready users (59%), as shown in Table 1. Additionally, i-Ready users achieved significantly lower fall standardized test z-scores (-0.63 vs. -0.16 in math and -0.50 vs. -0.11 in reading). i-Ready users were also significantly more likely to identify as Black and EL and significantly less likely to identify as White or Hispanic. i-Ready users were also significantly more likely to be in lower or upper elementary compared to middle and high school.

Table 1

Student Characteristics by i-Ready Usage

	Not i-Ready User	i-Ready User
Fall MAP Math Z-Score	-0.16	-0.63*

	(1.18)	(1.11)
Fall MAP Reading Z-Score	-0.11	-0.50*
	(1.23)	(1.12)
Asian	0.07	0.07*
	(0.25)	(0.25)
Black	0.59	0.70*
	(0.49)	(0.46)
White	0.20	0.15*
	(0.40)	(0.36)
Hispanic	0.11	0.05*
	(0.32)	(0.21)
Other Race	0.03	0.04*
	(0.18)	(0.19)
Female	0.49	0.50*
	(0.50)	(0.50)
FRLM	0.59	0.67*
	(0.49)	(0.47)
ELL	0.17	0.19*
	(0.37)	(0.40)
Emotional disability	0.02	0.02*
	(0.15)	(0.12)
Intellectual disability	0.02	0.01*
	(0.14)	(0.11)
Physical disability	0.00	0.00*
	(0.04)	(0.02)
Any disciplinary incidents	0.00	0.04*
	(0.02)	(0.20)
Lower elementary	0.31	0.55*
	(0.46)	(0.50)
Upper elementary	0.16	0.28*
	(0.37)	(0.45)
Middle school	0.24	0.17*
	(0.43)	(0.37)
High school	0.29	0.00*
	(0.45)	(0.01)
Observations	94,240	27,717

Note. * Significant differences between groups at the 0.05 level

Overall, we observed almost 28 thousand cases where students enrolled in i-Ready, which translated into 41 percent of students participating during years when i-Ready was available at their school and grade level. Much of the disparity in participation occurred in middle school grades, where we observed lower rates of usage, indicating teachers might have selectively assigned certain students to use i-Ready instead of universal enrollment. Additionally, some elementary teachers within schools with access to i-Ready appear to have opted not to use the platform.

Despite differential rates of any i-Ready use by school status, students who used i-Ready completed a comparable number of lessons and had similar mean lesson duration and percentage of lessons passed, whether they attended a priority school or not. On average, i-Ready users completed 26 reading and 20 math i-Ready lessons during SY 2021–22. Importantly, 99% of students who were assigned any i-Ready lesson, passed at least five lessons in each subject, indicating that after being assigned to i-Ready, the vast majority of students continued to use the program for the minimum of one instructional week. Each lesson took students, on average, 20 minutes (in reading) to 25 minutes (in math) to complete, with i-Ready users passing approximately 75% of reading lessons and 81% of math lessons begun. Additionally, 16% of reading lessons and 19% of math lessons were teacher-assigned versus i-Ready-assigned. The district provided schools autonomy in how they implemented i-Ready. We were unable to gather data on implementation practices by school, beyond the previously discussed user data collected by the i-Ready platform.

Table 2

i-Ready Usage by School Type During SY 2021–22

	Ever CSI	Horizon School	Neither	All
Any i-Ready Use	0.33*	0.35*	0.10	0.14
	(0.47)	(0.48)	(0.29)	(0.35)
Number of Reading Lessons	26.46*	22.88*	25.81	25.83
	(24.50)	(20.42)	(23.03)	(23.60)
Mean Reading Lesson Duration	18.41*	17.76*	21.46	19.51
	(10.89)	(10.90)	(14.29)	(13.04)
Reading Lesson Passed (%)	0.74	0.74	0.74	0.75
	(0.22)	(0.22)	(30.29)	(0.22)
Reading Lessons Assigned by Teacher (%)	0.16	0.18*	0.13	0.16
	(0.26)	(0.29)	(0.26)	(0.27)
Number of Math Lessons	16.61*	16.93*	20.09	19.56
	(15.83)	(17.25)	(20.25)	(19.92)
Mean Math Lesson Duration	23.27*	23.60*	26.37	24.48
	(10.44)	(10.37)	(14.14)	(12.13)
Math Lesson Passed (%)	0.80*	0.79*	0.83*	0.81
	(0.22)	(0.22)	(0.20)	(0.21)
Math Lessons Assigned by Teacher (%)	0.18	0.20*	0.15	0.19
	(0.28)	(0.29)	(0.27)	(0.29)
Observations	15,359	15,393	13,123	27,717

Note. * Significant differences between ever CSI or Horizon status and the rest of the sample at the 0.05 level

Analysis

We used OLS regression, school fixed effects, and inverse probability-weighted regression adjustment (IPWRA) models to examine the relationship between any i-Ready usage and achievement test score growth. We also estimated models that added an indicator for

whether any lessons were teacher-assigned, which are manually assigned to students by their teachers, versus automatically assigned lessons based on the adaptive learning platform. We then used dose-response functions to examine differential associations with achievement growth by number of i-Ready lessons. Lastly, we conducted an analysis of heterogeneous associations by running each model limiting the sample to subgroups of interest.

OLS Regression (with Grade and Year Fixed Effects)

To estimate the extent to which student use of online instructional materials was associated with improved student achievement growth in the post-pandemic era, we estimated an OLS regression model comparing student outcomes accounting for i-Ready access using data from SY 2021–22 and SY 2022–23 (eq. 1). Data were limited to kindergarten through ninth grade, since no i-Ready use was observed in tenth through twelfth grades.

$$score_{igt} = B_{0\,+}B_1 iReady_{it} + B_2 days_{it} + B_3 score_{it-1} + X_{it}B + \theta_g + \sigma_t + \varepsilon_{igt} \quad (1)$$

We estimated separate models for math and reading scores. All models control for the number of days between the beginning and end-of-semester test, lagged test scores from tests administered at the beginning of the school year, a vector of individual-level student characteristics (X_{it}), grade fixed effects (θ_g), and year fixed effects (σ_t). Student characteristics include student race/ethnicity and gender as well as FRPM, EL, and identified disability status (separated into emotional, intellectual, or physical disability). We also accounted for whether the student received any disciplinary referrals. All models used robust standard errors clustered at the school level.

Next, given the district policy that provided earlier i-Ready access to some schools over others, we estimated the same model shown in eq. 1 adding school fixed effects (λ_s), as shown in eq. 2.

$$score_{isgt} = B_{0\,+}B_1 iReady_{it} + B_2 days_{it} + B_3 score_{it,n-1} + X_{it}B + \lambda_s + \theta_g + \sigma_t + \varepsilon_{isgt} \quad (2)$$

We estimated eq. 2 twice, once with all cases and once limiting data to cases on common support from the propensity score analysis. Removing cases off common support has the benefit of preventing outliers without viable comparison cases from skewing estimates but reduces sample size and limits generalizability. More information on the proportion of cases removed due to this specification is provided when discussing IPWRA modeling below.

IPWRA Analysis

When implementing the OLS regression model, concerns remain related to treatment and comparison group imbalance, which can introduce bias into estimates. To minimize this concern, we also employed IPWRA to control for the extent to which there were systematic differences in whether a student used i-Ready based on both pre-treatment and fixed characteristics. The principal benefit of IPWRA includes balancing the treatment and comparison groups on a vector of relevant observable variables, which often results in dropping cases off common support that are so extreme that there are no comparable cases.

To implement this approach, we first estimated the likelihood of receiving treatment (i.e., using i-Ready or having a teacher-assigned lesson) using logistic regression conditioned on the vector of baseline school-level covariates (X_{it}) included in eq. 1 (see also Table 3) related to the prior achievement, socio-demographic characteristics, grade, year, and school CSI/Horizon status (see eq. 3; Rosenbaum & Rubin, 1983).

$$\Pr(z_i=1|X_i)=\frac{1}{(1+\exp[-(X\beta)])} \quad (3)$$

Table 3

Predicting Treatment Variables From Matching Covariates

	Treatment Variables			
	Any Math i-Ready	Any Reading i-Ready	Ever Teacher-assigned (Math)	Ever Teacher-assigned (Reading)
Fall Same-Subject MAP	-0.05***	-0.04***	0.05***	0.01
Inst. Days between Tests	0.01***	0.01***	0.02***	0.02***
Race/Ethnicity (Other Baseline)				
- Black	0.12***	0.20***	0.42***	0.42***
- White	-0.61***	-0.59***	-0.87***	-0.96***
- Hispanic	-0.66***	-0.48***	-0.65***	-0.41**
Female	0.04***	0.07***	0.07***	0.07***
Homeless	-0.38***	-0.39***	-0.20*	-0.25**
FRLM	0.13***	0.15***	0.05**	0.06**
Disability	-0.16***	-0.14***	-0.25***	-0.26***
EL	0.40***	0.50***	0.32***	-0.03
Grade (K Baseline)				
- 1	0.11***	0.10***	0.59***	0.73***
- 2	0.21***	0.24***	1.02***	1.19***
- 3	0.27***	0.36***	1.35***	1.42***
- 4	0.21***	0.31***	1.59***	1.36***
- 5	0.13	0.24***	1.43***	1.36***
- 6	-0.42***	-0.32***	-0.55***	0.01
- 7	-0.88***	-0.71***	-0.07	-0.19***
- 8	-1.01***	-0.85***	0.19***	0.33***
- 9	-8.65***	-8.61***	N/A	N/A

Year (2021–22 Baseline)				
- 2022–23	0.21***	0.36***	0.06**	0.31***
Horizon school	1.08***	1.19***	0.88***	1.00***
Ever CSI	1.22***	1.12***	0.58***	0.52***
Number of cases	105,970	96,280	95,809	86,612

Propensity scores were calculated using matching with a 0.01 caliper, no replacement, and limited to cases on common support. This method resulted in an 81–82% reduction in bias when estimating any i-Ready use and a 77–79% reduction in bias when estimating any teacher-assigned i-Ready lessons (see Table 4, Figure 1). Approximately 5% of the analytic sample was dropped when estimating any i-Ready use due to being outside the range of common support. The sample was more balanced when estimating whether a student had any teacher-assigned i-Ready lessons, which resulted in dropping less than 0.01% of cases.

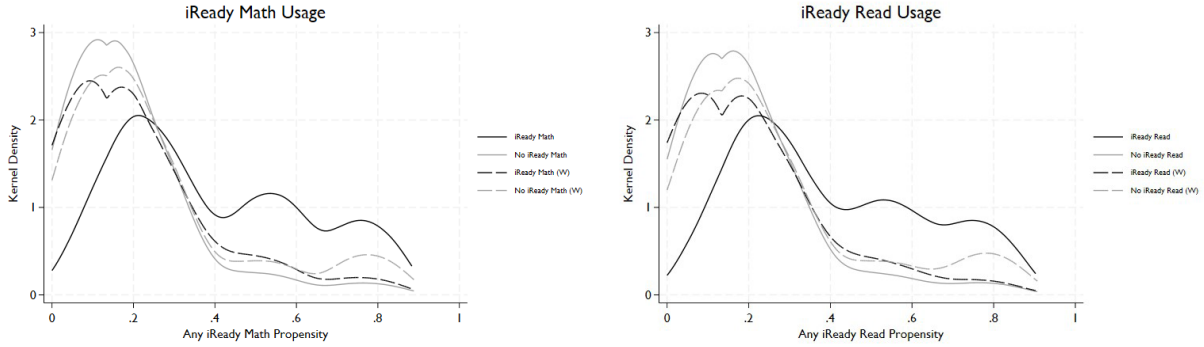
Table 4

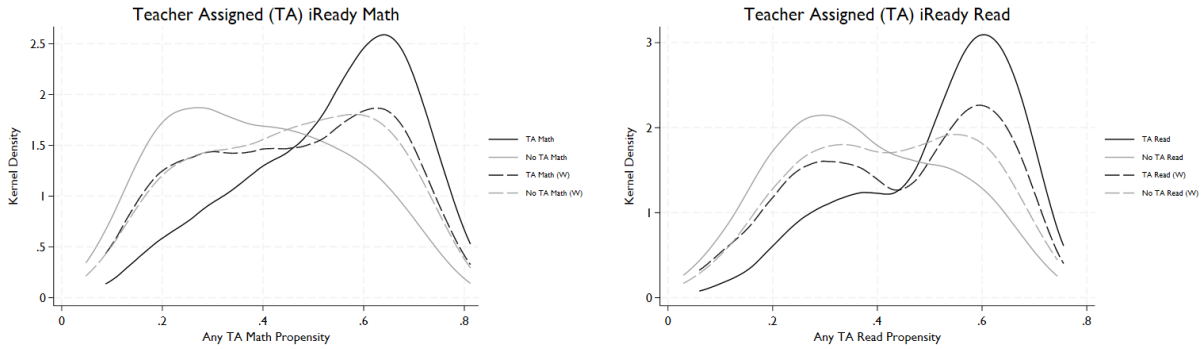
Propensity Score Matching Reduction in the Bias

		Off Support	LR chi2	Mean Bias	% Bias	Variance Ratio
Any Math i-Ready	Unmatched	---	12045.74	27.6	86.3	1.96
	Matched	5,221	512.13	5.2	23.5	1.38
Any Read i-Ready	Unmatched	---	10614.72	27.0	84.0	2.04
	Matched	5,263	418.83	4.9	21.9	1.48
Ever Teacher-assigned (Math)	Unmatched	---	7040.38	23.4	92.9	0.78
	Matched	72	176.26	3.5	18.8	1.08
Ever Teacher-assigned (Read)	Unmatched	---	5761.78	23.6	87.1	0.93
	Matched	2	186.94	3.2	20.3	1.01

Figure 1

Kernel density Plots of Propensity Distribution Before and After Matching





The likelihood ratio chi-squared test results show a substantial decrease in differences between groups on matching variables. The mean bias column reports the difference in means between the treatment and comparison group after accounting for the overall spread of each group. For each treatment variable, the mean bias between groups decreased dramatically. The matched samples had mean bias ranging from 4.7 to 9.7 compared to 16.8 to 27.6 for the unmatched sample. The estimated percent bias remaining in the sample similarly decreased between the unmatched and matched samples. The matched models estimating any i-Ready use (in math and reading) as well as whether the teacher ever assigned a lesson in reading fell below the 25.0 rule of thumb, while the matched model estimating whether the teacher ever assigned a lesson in math was approaching that threshold at 36.5% bias. For well-balanced groups, it is also desirable to have a variance ratio between 0.5 and 2, with a ratio of 1 being ideal to meet the assumptions required for OLS to be the best linear unbiased estimator (Rubin, 2001). The importance of a balanced variance ratio has also been demonstrated using simulated data where the true value was known (Rubin, 2001). The matched models estimating any i-Ready (in math and reading) as well as whether the teacher ever assigned a lesson in math fell within this range. The matched model estimating whether a teacher ever assigned an i-Ready lesson in reading showed a small improvement in the variance ratio but remained below the 0.5 threshold. Lastly, we identified substantial overlap in propensity scores between treatment and control groups visually, with the weighted propensity score distributions contributing to additional improvements in the distribution of propensity scores between groups, which is required to minimize bias (Murnane & Willett, 2011).

After estimating the likelihood of receiving each treatment, we used the resulting propensity score to fit a weighted regression model with covariate adjustment. This model was identical to the OLS regression equation presented in equation one apart from the inclusion of the weights generated from the matching process described above. More specifically, when assigning weights, treatment participants received a weight of $1/(\hat{\rho})$, while control participants received a weight of $1/(1-\hat{\rho})$ (Imbens & Wooldridge, 2009; Murnane & Willett, 2011). The advantage of this doubly robust method is that the estimates will be unbiased if either the propensity score or regression adjusted models are correctly specified.

To examine our second research question, we estimated separate OLS and IPWRA (eqs. 1–3) that accounted for whether any teacher assigned i-Ready lesson as the treatment in addition to any i-Ready use. If a lesson was not teacher assigned, then the lesson was assigned by the automated i-Ready system.

Dose-response Function

For the second research question, we also estimated dose-response functions to estimate the effect of different doses (or amount of exposure) to i-Ready; this approach is appropriate for use when assignment to treatment is non-random and accommodates continuous treatment measures (Cerulli, 2012). For these functions, we consider the number of i-Ready lessons assigned as the continuous treatment variable. We estimate two functions, one where the dose is zero (eq. 4) and one where the dose is not zero and continuous (eq. 5).

$$w = 0 \rightarrow y_0 = B_0 + B_1 days_{it} + B_2 score_{it,n-1} + X_{it}B + \varepsilon_{it} \quad (4)$$

$$w = 1 \rightarrow y_1 = B_0 + B_1 days_{it} + B_2 score_{it,n-1} + X_{it}B + h(t) + \varepsilon_{it} \quad (5)$$

Equation 5 adds to equation 4 the term *h(t)*, which is a response function that accounts for the dose (i.e., how many i-Ready lessons the student was assigned). We subsequently estimate and graph the resulting non-linear response curves. Given that the modal number of lessons assigned were 20–25 (depending on the subject) with standard deviations of 20–24, we chose to graph only up to 100 lessons to prevent attempts to interpret estimates where there was insufficient data to support robust findings. This choice resulted in dropping no more than 1% of the sample.

As a sensitivity check we generated graphs including these outliers; maximum average treatment effects and trends were comparable whether dropping or including outliers. As with previous analyses, results are associational in nature. We also examined correlations between the number of assigned i-Ready lessons and fall MAP test scores to determine whether students might be systematically assigned more or fewer i-Ready lessons based on their prior achievement level, which could bias the resulting estimates. Among students assigned any i-Ready lessons, we observed no significant correlation between the number of math lessons assigned and students' fall MAP math score ($r = 0.01$, $p = 0.27$). We observed a significant, negative correlation in reading ($r = -0.05$, $p < 0.01$). This translates into being assigned one fewer i-Ready reading lesson for each standard deviation increase in MAP reading test scores. Although significant, this is a low magnitude relationship given that on average, i-Ready users were assigned 20 reading lessons. For this reason, we are less concerned that systematic assignment of i-Ready lessons by prior achievement level might be biasing the resulting estimates.

Heterogeneity Analysis

Lastly, we examined potential heterogeneous treatment effects by estimating eqs. 1–3 limited to each student subgroup of interest (i.e., gender and race/ethnicity as well as EL, FRPM, identified disability, and disciplinary status). We also examined separately students who did not meet state standards on the prior year state level and grade level (lower elementary, upper elementary, middle, and high school). Additionally, we estimated the dose-response function analysis for students with various prior levels of achievement and by FRPM status.

Limitations

Before proceeding to our findings, we reiterate the limitations of our empirical strategy. Findings are based on data from one metro-area district, which has its own unique contextual and demographic factors that may not generalize to all settings. Our analyses are descriptive versus causal as we cannot fully account for endogenous variation. Relatedly, we were unable to fully understand or account for selection into treatment. Among the approximately 67,000 instances where peers in a students' school-grade-year were assigned to use i-Ready, only around 28,000 students were assigned lessons. Given low universality, we estimated models that examined whether the students' school-grade-year had access to i-Ready interacted with whether that student used i-Ready. Estimates for any use of i-Ready remained comparable in directionality, magnitude, and significance, minimizing our concern that not being able to fully account for selection into treatment within school-grade-year bands might be biasing our results.

Importantly, we were unable to collect data on or account for other recovery interventions occurring during the same period that might have been targeting similar schools. And, lastly, we conducted an intent-to-treat (ITT) analysis that examined all students assigned to complete any i-Ready lesson (versus those that actually completed an i-Ready lesson). ITT is an inherently conservative approach and thus may underestimate the true benefit for students who are adequately supported and motivated to fully engage. However, we felt conducting this analysis was appropriate to inform district decision-making. We attempt to provide insight into the possible maximum benefit for students who engage fully with the i-Ready platform by estimating dose-response functions with average treatment effects across the number of i-Ready lessons assigned.

Results

Across all model specifications, we identified a positive association between i-Ready usage and students' math and reading standardized test scores, as shown in Table 5. Estimates from the OLS models with school fixed effects and the IPWRA model were significant and ranged from 0.03 to 0.04 standard deviations higher test scores in reading and 0.04 to 0.05 standard deviations higher test scores in math among students who used i-Ready. Such increases translate into roughly two additional weeks of instructional growth in math and nearly three additional weeks in reading for the median student in our sample (i.e., a 5th grader). Given that the district prioritized providing low-income schools access to i-Ready first, differences in estimates between models that do and do not include school fixed effects may indicate base models were not fully able to parse out potentially deflating confounding influences. Additionally, teacher-assignment of any i-Ready math lessons was associated with 0.02 to 0.04 standard deviations higher test scores, than students who used i-Ready with only computer-assigned lessons. Estimates were larger in magnitude and significant when including school fixed effects and using an IPWRA approach.

Table 5

Associations Between Any i-Ready Usage, Teacher-Assigned Lessons, and MAP Z-Scores

	OLS	School FE	School FE w/ C.S.	IPWRA
Any i-Ready Usage (Math)	0.02	0.04**	0.04**	0.05**

	(0.01)	(0.02)	(0.02)	(0.02)
Observations	103711	103711	98551	98551
Adjusted R-squared	0.827	0.829	0.830	0.839
Any i-Ready Usage (Reading)	0.02	0.03***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.02)
Observations	94534	94534	89334	89334
Adjusted R-squared	0.783	0.786	0.789	0.806
Any Teacher Assigned (Math)	0.03**	0.05***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	103711	103711	94393	94393
Adjusted R-squared	0.827	0.830	0.829	0.810
Any Teacher Assigned (Reading)	0.03*	0.04**	0.04***	0.04**
	(0.02)	(0.01)	(0.02)	(0.02)
Observations	94534	94534	85533	85533
Adjusted R-squared	0.784	0.784	0.788	0.771
Student Covariates	Yes	Yes	Yes	Yes
Grade Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
School Fixed Effect	No	Yes	Yes	Yes

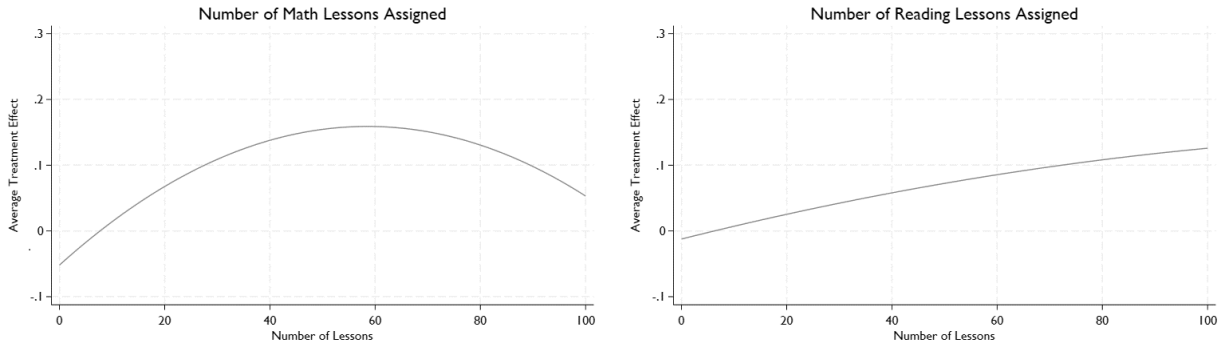
Note. * p < 0.10, * p < 0.05, * p < 0.01

To place these associations in context, we examined i-Ready costs and counterfactuals. Publicly available data suggests that districts pay about $30 per student annually for a user license. At this rate, we estimate that the district paid roughly $831,510 (around $415,000 a year) to serve the sample of students in our study, roughly equivalent to the salary cost of five additional teachers annually. The same district partner also implemented teacher-led "extended learning time" and tutoring models as part of their COVID-19 recovery strategy. These interventions did not yield significant achievement growth for students overall with the exception of struggling middle school students who experienced modest growth when dedicating at least 3 hours per week to academic recovery (Sass, 2024). Thus, in this district's case and despite the cost, i-Ready was able to successfully support accelerated student achievement growth beyond that observed when studying other recovery interventions.

Next, we estimated dose response functions to examine variations in average treatment effects conditional on the number of lessons assigned, as shown in Figure 2. In math, average treatment effects hit a ceiling of around 0.18 standard deviations, or roughly eight weeks of instructional growth, among students who were assigned 60 or more lessons. By contrast, we identified no ceiling in reading, with average treatment effects continuing to increase in magnitude up to at least 100 assigned lessons. Notably, average treatment effects are never negative in reading, with low magnitude negative associations in math switching to positive once students were assigned at least 10 lessons.

Figure 2

Dose-Response Function for MAP Z-Scores by Number of Lessons Assigned



Lastly, we examined the extent to which there might be differential effects of i-Ready usage, teacher lesson assignment, and the number of i-Ready lessons assigned by subgroup. We report estimates only for the IPWRA model as it is the most rigorous model we can estimate on our full sample. When examining any i-Ready use by subgroup, as shown in Table 6, we continue to identify a significant, positive association with achievement growth comparable to the associations observed across the entire sample for students identified as Black, male, receiving FRPM, and/or with identified intellectual disabilities**.** Black, male, and students receiving FRPM experienced 2.2 additional weeks of instructional growth in math, and students with intellectual disabilities saw nearly 8 weeks of instructional growth in math using i-Ready. We see similar gains in reading. Black and male students experienced 3.5 weeks of instructional growth; students receiving FRPM yielded 2.8 weeks of instructional growth, and those identified with intellectual disabilities experienced 14 weeks of instructional growth. Additionally, we identified significant, positive associations among female students as well as students in lower elementary grades and/or with prior achievement in the middle third of district test scores in math but not reading. Across all groups and subject specifications, we failed to identify any statistically significant negative associations.

Table 6

Associations Between Any i-Ready Usage and MAP Z-Scores by Subgroup

	Math		Reading	
	N	IPWRA	N	IPWRA
Lowest 3rd prior achievement	39567	0.04	33621	0.03*
		(0.03)		(0.02)
Middle 3rd prior achievement	33146	0.06***	30440	0.02
		(0.02)		(0.02)
Highest 3rd prior achievement	30998	0.01	30473	0.03*
		(0.01)		(0.02)
Asian	7254	0.03	6554	-0.00
		(0.03)		(0.04)
Black	56366	0.05**	53423	0.05***
		(0.03)		(0.02)
White	11779	0.04	10682	0.05
		(0.04)		(0.05)
Hispanic	24724	0.05	20586	0.03

		(0.03)		(0.02)
Other race	4504	-0.02	4071	0.00
		(0.04)		(0.05)
Female	50553	0.03**	46311	0.02
		(0.02)		(0.01)
Male	53158	0.05**	48223	0.05**
		(0.03)		(0.02)
FRPM	60166	0.05**	54623	0.04***
		(0.02)		(0.01)
ELL	23267	0.04	19506	0.02
		(0.04)		(0.02)
Emotional disability	1702	0.14	1549	0.09
		(0.09)		(0.10)
Intellectual disability	1009	0.18**	919	0.20***
		(0.09)		(0.07)
Physical disability	110	1.22	103	0.59
		(0.83)		(0.39)
Any disciplinary incident	5768	0.00	5215	-0.05
		(0.05)		(0.06)
Lower elementary	43050	0.05**	39316	0.02
		(0.02)		(0.02)
Upper elementary	21663	0.03	19440	0.05*
		(0.02)		(0.03)
Middle school	29747	0.02	26779	0.03
		(0.03)		(0.02)

When examining students with any teacher assigned i-Ready lessons by subgroup, we identified significant, positive associations of having any teacher-assigned lessons among students from the lowest-third prior achievement level (in math and reading) and from the middle-third prior achievement level (in math only), as shown in Table 7. Interestingly, we did not identify significant, positive associations among students in the upper-third prior achievement level in either subject when the teacher assigned lessons. Additionally, having any teacher versus solely i-Ready-assigned lessons was associated with significantly higher student achievement growth in both subjects among students identified as male, with disciplinary incidents, and/or in a lower elementary grade across both subjects. Only in math, we also identified positive associations of having any teacher-assigned lessons among students identified as Black, female, receiving FRPM, and/or and in middle school. Only in reading, we also identified positive associations of having any teacher-assigned lessons among students identified as White and upper elementary school.

Table 7

Associations Between Any Teacher Assigned Lessons and MAP Z-Scores by Subgroup

	Math		Reading	
	N	IPWRA	N	IPWRA

Lowest 3rd achievement	10255	0.08**	9433	0.11**
		(0.03)		(0.04)
Middle 3rd achievement	7894	0.08***	7555	0.02
		(0.02)		(0.03)
Highest 3rd achievement	5712	0.01	5808	0.03
		(0.04)		(0.04)
Asian	1770	0.10	1535	-0.02
		(0.08)		(0.05)
Black	16381	0.08***	15958	0.07*
		(0.02)		(0.03)
White	1160	0.19	974	0.21**
		(0.12)		(0.09)
Hispanic	3798	-0.01	3616	0.01
		(0.06)		(0.08)
Other race	899	-0.04	841	0.15
		(0.06)		(0.09)
Female	11801	0.08***	11397	0.01
		(0.02)		(0.04)
Male	12060	0.06***	11399	0.11***
		(0.02)		(0.03)
FRPM	15828	0.06***	15355	0.05*
		(0.02)		(0.03)
ELL	4913	0.07	4655	0.03
		(0.04)		(0.06)
Emotional disability	358	0.10	334	0.20
		(0.17)		(0.16)
Intellectual disability	278	-0.15	N/A	N/A
		(0.25)		
Any disciplinary incidents	883	0.12**	899	0.20**
		(0.06)		(0.09)
Lower elementary	13452	0.11**	12854	0.10**
		(0.04)		(0.04)
Upper elementary	7012	0.04	3407	0.10**
		(0.02)		(0.04)
Middle school	3396	0.04***	6535	0.03
		(0.01)		(0.04)

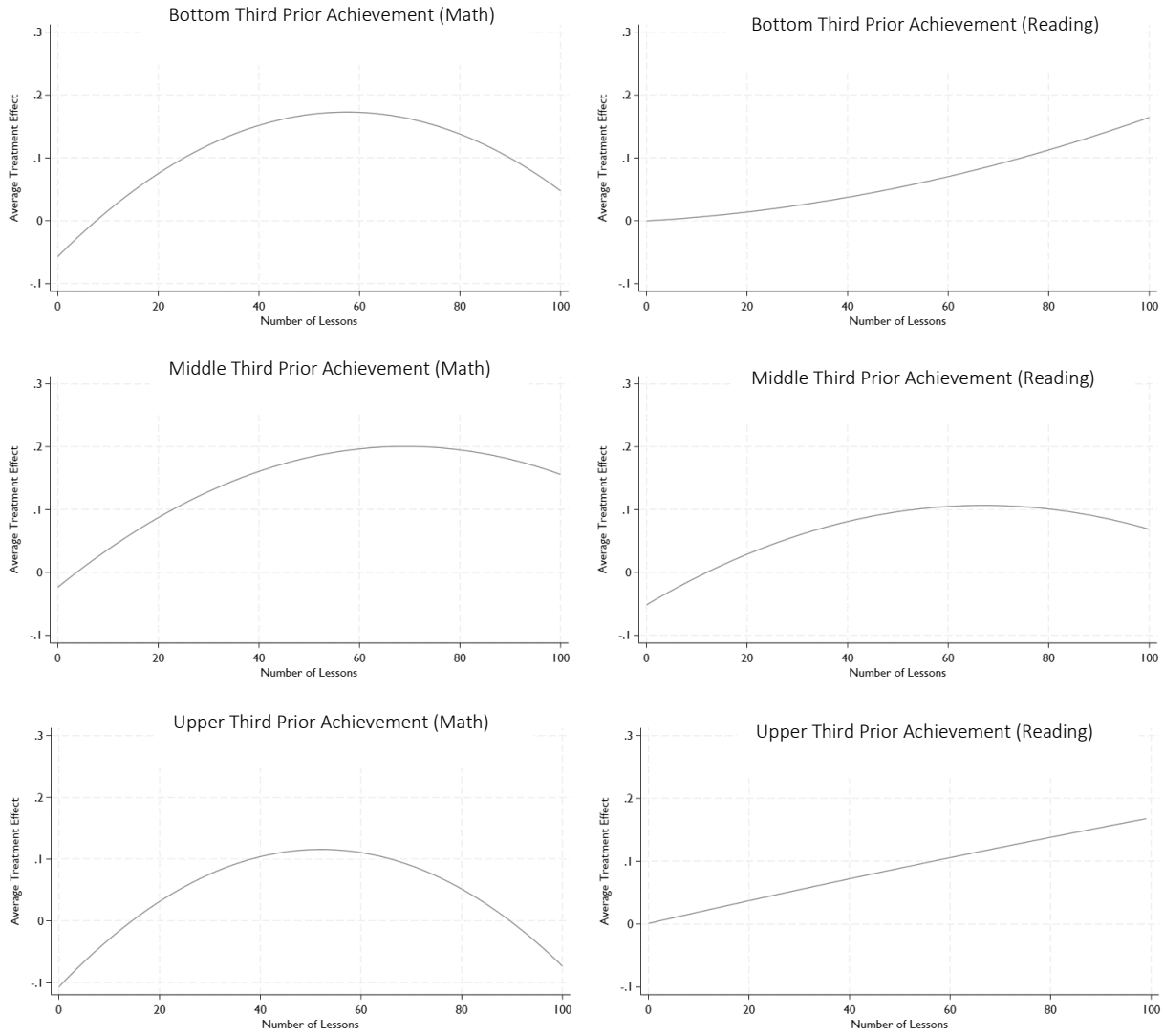
Note. Insufficient data to calculate for students identified as having a physical disability for either subject. Insufficient data to calculate for students identified as having a intellectual disability for reading.

Additionally, we examined associations between the number of assigned i-Ready lessons and student achievement growth by prior achievement level (in Figure 3) and FRPM status (in Figure 4). Dose-response functions were relatively similar across prior achievement levels in math with maximum treatment effects observed around 50 lessons assigned. However, students in the upper third of prior math achievement experienced the steepest drop in average treatment effects beyond that point, followed by students in the lowest third of prior achievement. Students in the middle third of prior math achievement were least likely to experience negative associations with use across the number of assigned lessons spectrum, the highest maximum treatment effect, and the smallest decline in average treatment effects from that point. In contrast, we observed the opposite pattern in reading with only students in the middle third of reading prior achievement experiencing a ceiling effect (at around 70 assigned lessons). Students in the

lower and upper third of reading prior achievement experienced the largest maximum treatment effects at high intensity use of around 0.2.

Figure 3

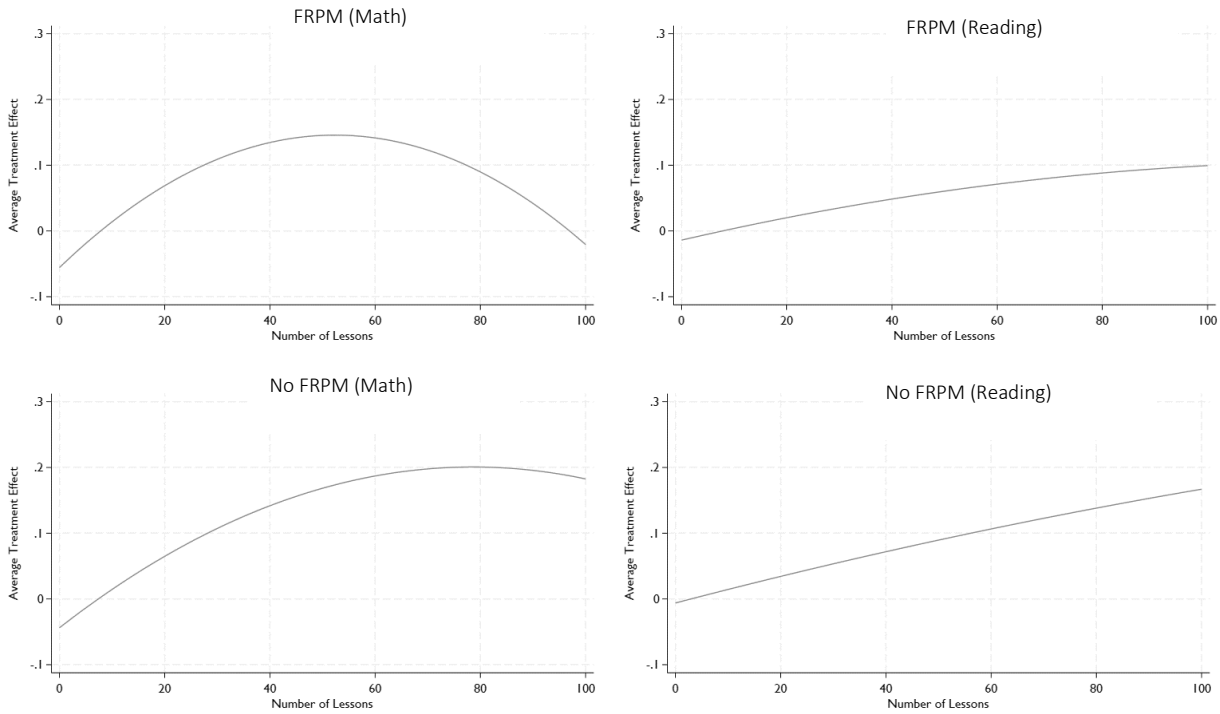
Dose-Response Function for MAP Z-Scores by Prior Achievement



When examining dose-response functions for number of lessons assigned by FRPM status, we identified a ceiling effect (in math) and lower average treatment effects (in reading) among students receiving FRPM. More specifically, the trend between increasing student achievement growth as more i-Ready math lessons were assigned started reversing at around 60 lessons for students receiving FRPM. In reading, the average treatment effect at 100 assigned lessons was only around 75% of the average treatment effect achieved by students not receiving FRPM at that level of use.

Figure 4

Dose-Response Function for MAP Z-Scores by FRPM Status



Discussion

This study provides an impact analysis of i-Ready usage and associations with student achievement growth across different student subgroups and i-Ready content areas. As a widely used virtual learning tool with features similar to other learning platforms on the market, better understanding of platform strengths and limitations can support school district decision-making. Online learning platforms such as i-Ready have the potential to be useful tools to enhance student achievement recovery because they can offer personalized learning that supplements traditional face-to-face instruction. However, empirical research offers mixed findings on their effectiveness, noting various conditions in which they are effective. We discuss the answers to our research questions in turn and provide recommendations for education leaders below.

First, we find that student use of online instructional materials is associated with a 0.04 to 0.05 standard deviation increase in student achievement growth (in our preferred IPWRA models). This translated into roughly two to three additional weeks of instructional growth. The growth observed is particularly important given that i-Ready users in our sample have lower fall standardized test scores in math and reading and are more likely to attend a priority school. The finding conflicts with previous research suggesting negative outcomes for students with lower prior achievement levels (Ahn & McEachin, 2017; Besecker et al., 2020; Fitzpatrick et al., 2020; Gonzales et al., 2020; Heinrich et al., 2019; Woodworth et al., 2015), but aligns with research finding that students perform better on achievement assessments when using adaptive online learning platforms as a supplement (versus replacement) to traditional, face-to-face instruction

(Heppen et al., 2011; Wiburg et al., 2016; Connor et al., 2018). Additionally, we observe larger positive associations among students whose teachers assigned at least one i-Ready lesson in addition to solely using platform-assigned lessons. Students across demographic groups, ability level, and grade level appear to benefit from teacher-assigned online assignments, indicating that teacher input is critical to the effectiveness of online learning platforms.

We find that students experience differential rates of achievement using the i-Ready platform, largely by sociodemographic versus prior achievement or grade-level characteristics. Students who identify as Black, male, FRLM-eligible, or with intellectual disabilities experience more significant improvements using the online learning platform than their peers, gaining up to 14 additional weeks of instructional growth. While these findings do not align with previous research that more advantaged groups are more likely to benefit from online learning, they seem to suggest that i-Ready can assist populations of greater need and of fewer resources. One potential reason why we did not find inequitable outcomes may be the district's investment in one-to-one devices and hotspots for students to mitigate disparities in access. i-Ready users in our sample are more likely to identify as Black, an English Learner, and FRPM-eligible in an elementary grade, so the findings may also reflect the unique demographics of study context. Nevertheless, the gains of students from historically marginalized groups while using i-Ready offers insight into its usefulness in addressing both pandemic-related achievement recovery and historical demographic-related achievement gaps.

Surprisingly, we find only minimal differential achievement related to i-Ready usage based on prior achievement or grade level. Previous research contends that older students with stronger self-regulation skills and those with higher prior achievement levels are more likely to benefit from online learning platforms such as i-Ready (Darling-Aduana et al., 2022; Heinrich et al. 2019; Munoz-Najar et al., 2021; Warschauer & Matuchniak, 2010; Wijekumar et al. 2014), but our study suggests that students of various grade levels can equally benefit from online learning platforms. In fact, our study demonstrates i-Ready's particular usefulness in supporting students in elementary grade levels, as it was largely used in second- through fifth-grade classrooms, and we observe the largest gains (nearly 8 weeks) in math for students in lower elementary grades. The only significant variation observed by prior achievement level is slightly stronger achievement gains in math among students in the middle third prior achievement group.

Finally, the study reveals the achievement limits of adaptive online platforms. Students experience diminishing returns in math after completing around 50 or more lessons (between the fall and winter MAP testing window), apart from students who perform amongst the middle third of the district's math test score distribution. Conversely, students continue to experience gains in reading beyond this point and up to at least 100 assigned lessons, but here students in the middle third of the district's reading test score distribution begin to experience diminishing returns after completing roughly 70 lessons. Similar trends emerge when we observe the dosage effects for FRPM-recipients. Overall, the findings are consistent with previous research on dosage-response functions when using online instructional tools that suggest 40 to 100 hours of usage are key thresholds for positive learning outcomes for students (Heinrich et al., 2014; Darling-Aduana & Heinrich, 2018). However, findings also reveal that expanding beyond the thresholds may not be a wise investment of instructional time or student effort.

The global pandemic forced a rapid shift in learning delivery and expanded the role of virtual learning in students' educational experiences. Online learning platforms such as i-Ready have become a part of schools' and teachers' instructional toolkit to serve students across Grades K–8 and ability levels. Our findings suggest that online learning platforms are valuable tools that school districts should maintain or adopt to aid in COVID-19 achievement recovery. Schools and districts that serve large historically marginalized populations could especially benefit from the investment, as our findings show that the platforms bode well for these students, so long as device and home internet access are ensured.

However, we caution districts against using online platforms as an "auto-pilot" replacement for classroom instruction. Adaptive, personalizing learning is a key feature of the i-Ready system and likely contributes to the achievement gains we observed but extending the adaptive learning beyond threshold points may not benefit students. What's more, students with the lowest and strongest math ability and median reading ability may begin to lose the academic benefits of the platform before their peers, so it's important that schools and districts support teachers in using the online platforms as complementary tools to in-person instruction in which teachers' discretion is used to assign online lessons. Our findings also show that students perform better when teachers monitor frequency of use and assign lessons strategically. Supporting teachers through additional training on how to best assign lessons and the strengths and weaknesses of the platforms could also aid in achievement recovery for students.

Scholars and practitioners alike have been critical of the progress and pace of academic recovery of students post-COVID-19, with some optimistic that students are beginning to meet and exceed their pre-pandemic learning levels. Others are more skeptical, arguing that students will need much more time and support to meet such outcomes. Online adaptive learning platforms such as i-Ready appear well-equipped to support recovery goals, with several logistical advantages over other recovery interventions, which tend to have higher costs and struggle with low uptake and participant stigma.

Declarations

Acknowledgement

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Ethics Statement

This study was conducted in accordance with recognized ethical standards. The study underwent IRB review at Georgia State University (Approval No. H22434), where it was determined not human subjects research.

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opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

AI Use Statement

The authors did not use generative artificial intelligence (AI) in the preparation of this manuscript.

Conflicts of Interest Statement

The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

Data Availability Statement

The data that support the findings of this study are available from the school district partner. But restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of the school district partner.

References

Ahn, J., & McEachin, A. (2017). Student enrollment patterns and achievement in Ohio's online charter schools. *Educational Researcher, 46*(1), 44–57.

Allensworth, E., & Schwartz, N. (2020). School practices to address student learning loss. Brief No. 1. *EdResearch for Recovery Project*.

Aucejo, E. M., & Romano, T. F. (2016). Assessing the effect of school days and absences on test score performance. *Economics of Education Review*, *55*, 70–87.

Augustine, C. H., McCombs, J. S., Pane, J. F., Schwartz, H. L., Schweig, J., McEachin, A., & Siler-Evans, K. (2016). *Learning from summer: Effects of voluntary summer learning programs on low-income urban youth. RAND Summer Learning Series. Research Report. RR-1557-WF*. RAND Corporation.

Barnum, M., & Belsha, K. (2023, October 2). Math test scores show some recovery from pandemic learning loss; reading scores stagnant. *Chalkbeat*. https://www.chalkbeat.org/2023/10/2/23896045/state-test-scores-data-math-reading-pandemic-era-learning-loss/

Basham, J. D., Smith, S. J., & Satter, A. L. (2016). Universal design for learning: Scanning for alignment in K–12 blended and fully online learning materials. *Journal of Special Education Technology, 31*(3), 147–155.

Besecker, M., Thomas, A., & Daley, G. (2020). Student engagement online during school facilities closures: An analysis of LA Unified secondary students Schoology activity from March 16 to May 22, 2020. *Los Angeles Unified School District Report*, 1–23.

Borup, J., Chambers, C. B., & Stimson, R. (2019). K–12 student perceptions of online teacher and on-site facilitator support in supplemental online courses. *Online Learning, 23*(4), 253–280.

Callen, I., Carbonari, M. V., DeArmond, M., Dewey, D., Dizon-Ross, E., Goldhaber, D., ... & Staiger, D. O. (2023). Summer school as a learning loss recovery strategy after COVID-19: Evidence from summer 2022. Working Paper No. 291-0823. *National Center for Analysis of Longitudinal Data in Education Research (CALDER)*.

Carbonari, M. V., Davison, M., DeArmond, M., Dewey, D., Dizon-Ross, E., Goldhaber, D., Hashim, A. K., Kane, T. J., McEachin, A., Morton, E., Patterson, T., & Staiger, D. O. (2022). *The challenges of implementing academic COVID recovery interventions: Evidence from the road to recovery project. Working Paper No. 275-1222.* National Center for Analysis of Longitudinal Data in Education Research (CALDER).

Carbonneau, K. J., Marley, S. C., & Selig, J. P. (2013). A meta-analysis of the efficacy of teaching mathematics with concrete manipulatives. *Journal of Educational Psychology*, *105*(2), 380.

Cerulli, G. (2012). *A continuous treatment model for estimating a Dose Response Function under endogeneity and heterogeneous response to observable confounders: Description and implementation via the Stata module "ctreatreg"*. National Research Council of Italy.

Checkoway, A., Gamse, B., Velez, M., & Linkow, T. (2013). *Evaluation of the Massachusetts Expanded Learning Time (ELT) initiative: Final study findings*. Society for Research on Educational Effectiveness.

Connor, C. M., Mazzocco, M. M., Kurz, T., Crowe, E. C., Tighe, E. L., Wood, T. S., & Morrison, F. J. (2018). Using assessment to individualize early mathematics instruction. *Journal of School Psychology, 66*, 97–113.

Darling-Aduana, J. (2021c). Authenticity, engagement, and performance in online high school courses: Insights from micro-interactional data. *Computers & Education, 167.* doi:j.compedu.2021.104175

Darling-Aduana, J., Good, A. G., & Heinrich, C. J. (2019). Mapping the inequity implications of help-seeking in online credit-recovery classrooms. *Teachers College Record, 121*(11), 1–40.

Darling-Aduana, J., & Heinrich, C. J. (2018). The role of teacher capacity and instructional practice in the integration of educational technology for emerging bilingual student. *Computers & Education, 126*, 417–432. doi:10.1016/j.compedu.2018.08.002

Darling-Aduana, J., Heinrich, C. J., Noonan, J., Wu, J., Enriquez, K. (2024). *Failing to learn from failure: The façade of online credit recovery assessments* (EdWorkingPaper: 10.26300). Annenberg Institute at Brown University.

Darling-Aduana, J., & Hemingway, K. (2022). Representation is not enough: Teacher identity and discretion in an asynchronous, scripted online learning environment. *Teachers College Record, 124*(9). doi:10.1177/01614681221132384

Darling-Aduana, J., Woodward, H. T., Sass, T. R., and *Barry, S. S.* (2022). Preferences, engagement, and achievement during crisis schooling in the COVID-19 era. *AERA Open, 8.* doi:10.1177/23328584221128035

Enyedy, N. (2014). *Personalized instruction: New interest, old rhetoric, limited results, and the need for a new direction for computer-mediated learning.* National Education Policy Center. Retrieved from http://nepc.colorado.edu/publication/personalized-instruction

Evidence for ESSA. (2025). *I-Ready personals instruction reading*. Retrieved from https://evidenceforessa.org/program/i-ready-personalized-instruction-reading/#

Fahle, E., Kane, T. J., Reardon, S.F., & Staiger, D. O. (2024). *The first year of pandemic recovery: A district-level analysis*. Center for Education Policy Research, Harvard University, and Educational Opportunity Project, Stanford University.

Figlio, D., Holden, K. L., & Ozek, U. (2018). Do students benefit from longer school days? Regression discontinuity evidence from Florida's additional hour of literacy instruction. *Economics of Education Review*, *67*, 171–183.

Fitzpatrick, B., Berends, M., Ferrare, J. J., & Waddington, R. J. (2020). *Virtual charter schools and online learning during COVID-19*. Brookings. https://www.brookings.edu/articles/virtual-charter-schools-and-online-learning-during-covid-19/

Fryer, Jr., R. G. (2016). The production of human capital in developed countries: Evidence from 196 randomized field experiments. In *Handbook of Economic Field Experiments* (Vol. 2, pp. 95–322). North-Holland.

Gates, A. (2024). *Teachers' perceptions of the impact of iReady of student reading achievement for students in Response to Intervention* [Doctoral dissertation]. Kennesaw State University. Retrieved from https://digitalcommons.kennesaw.edu/dissertations/26

Gershenson, S., & Lomax, E. (2021). *Learning recovery and a diverse workforce: A win-win for students hardest hit by COVID-19*. National Comprehensive Center at Westat.

Goldstein, D., Popescu, A., & Hannah-Jones, N. (2020, April 6). As school moves online, many students stay logged out. *New York Times*. https://www.nytimes.com/2020/04/06/us/coronavirus-schools-attendance-absent.html

Gonzales, M. M., & Jackson, I. (2020). Going the distance: What school administrators can learn from one-to-one laptop schools. *Journal of School Administration Research and Development, 5*, 55–60.

Hashim, A. K., Davison, M., Postell, S., & Isaacs, J. (2024). *High-dosage tutoring for academically at-risk students*. NWEA.

Heinrich, C. J., Burch, P., Good, A., Acosta, R., Cheng, H., Dillender, M., ... & Stewart, M. (2014). Improving the implementation and effectiveness of out-of-school-time tutoring. *Journal of Policy Analysis and Management, 33*(2), 471–494.

Heinrich, C. J., Darling-Aduana, J., Good, A. G., & Cheng, H. (2019). A look inside online educational settings in high school: Promise and pitfalls for improving educational opportunities and outcomes. *American Educational Research Journal, 56*(6), 2147–2188. doi:10.3102/0002831219838776

Heppen, J. B., Walters, K., Clements, M., Faria, A. M., Tobey, C., Sorensen, N., & Culp, K. (2011). *Access to Algebra I: The effects of online mathematics for grade 8 students* [NCEE 2012-402]. Washington, DC: National Center for Education Evaluation and Regional Assistance. https://eric.ed.gov/?id=ED527394

Holzman, M., & Duncan, M. (2022). *Impact of i-Ready personalized instruction on the Massachusetts Comprehensive Assessment System Achievement for grade 5 in English language arts and mathematics.* Curriculum Associates Research Report No. 07.

i-Ready. (2025). *Personalized learning in reading and mathematics.* Retrieved from https://www.curriculumassociates.com/programs/i-ready-learning/personalized-instruction

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature, 47*(1), 5–86.

Jacob, B., Berger, D., Hart, C., & Loeb, S. (2016). Can technology help promote equality of educational opportunities? *RSF: The Russell Sage Foundation Journal of the Social Sciences, 2*(5), 242–271.

Kaufman, J. H., & Diliberti, M. K. (2021). *Divergent and inequitable teaching and learning pathways during (and perhaps beyond) the pandemic: Key findings from the American Educator Panels Spring 2021 COVID-19 Surveys.* RAND Corporations.

Kraft, M. A., & Falken, G. T. (2021). A blueprint for scaling tutoring and mentoring across public schools. *AERA Open*, *7*.

Kraft, M. A., & Novicoff, S. (2022). Instructional time in U.S. public schools: Wide variation, causal effects, and lost hours. *Annenberg Institute at Brown University*.

Kogan, V., & Lavertu, S. (2021). *The COVID-19 pandemic and student achievement on Ohio's third-grade English Language Arts assessment.* Report prepared for the Ohio Department of Education.

Kuhfeld, M., & Lewis, K. (2022). *Student achievement in 2021–2022: Cause for hope and continued urgency*. NWEA.

Kuhfeld, M., Soland, J., Lewis, K., Ruzek, E., & Johnson, A. (2022). The COVID-19 school year: Learning and recovery across 2020–2021. *Aera Open*, *8*.

Lee, S., Kuo, L. J., Xu, Z., & Hu, X. (2022). The effects of technology-integrated classroom instruction on K–12 English language learners' literacy development: A meta-analysis. *Computer Assisted Language Learning, 35*(5–6), 1106–1137.

Lewis, K., & Kuhfeld, M. (2023). *Education's long COVID: 2022–23 achievement data reveal stalled progress toward pandemic recovery*. Center for School and Student Progress at NWEA.

Liao, Y. C., Ottenbreit-Leftwich, A., Zhu, M., Jantaraweragul, K., Christie, L., Krothe, K., & Sparks, K. (2021). How can we support online learning for elementary students? Perceptions and experiences of award-winning K–6 teachers. *TechTrends, 65*(6), 939–951.

Lowes, S., Lin, P., & Kinghorn, B. R. (2016). Gender differences in online high school courses. *Online Learning, 20*(4), 100–117.

Markovitz, C. E., Hernandez, M. W., Hedberg, E. C., & Whitmore, H. W. (2022). Evaluating the effectiveness of a volunteer one-on-one tutoring model for early elementary reading intervention: A randomized controlled trial replication study. *American Educational Research Journal*, *59*(4), 788–819.

Mann, B., Li, W., & Besnoy, K. (2021). Digital divides: K–12 student profiles and online learning. *Education Policy Analysis Archives, 29*(112).

McKinnon, R. (2018). Wary of i-Ready. *Herald-Tribute.* Retrieved from https://www.heraldtribune.com/story/news/local/manatee/2018/09/22/more-teachers-less-tech-say-parents-wary-of-i-ready/10122809007/?gnt-cfr=1&gca-cat=p&gca-uir=true&gca-epti=z119055a11xx50c11xx50d00----v119055b00xxxxd11xx65&gca-ft=242&gca-ds=sophi

Munoz-Najar, A., Gilberto, A., Hasan, A., Cobo, C., Azevedo, J. P., & Akmal, M. (2021). *Remote learning during COVID-19: Lessons from today, principles for tomorrow.* World Bank.

Murnane, R. J., & Willett, J. B. (2011). *Methods matter: Improving causal inference in educational and social science research.* Oxford University Press.

Nickow, A., Oreopoulos, P., & Quan, V. (2024). The promise of tutoring for PreK–12 learning: A systematic review and meta-analysis of the experimental evidence. *American Educational Research Journal*, *61*(1), 74–107.

NWEA. (2025). *We're NWEA.* Retrieved from https://www.nwea.org/about/

Pace, J. R., & Mellard, D. F. (2016). Reading achievement and reading efficacy changes for middle school students with disabilities through blended learning instruction. *Journal of Special Education Technology, 31*(3), 156–169.

Pier, L., Christian, M., Tymeson, H., & Meyer, R. H. (2021). *COVID-19 impacts on student learning: Evidence from interim assessments in California.* Policy Analysis for California Education. https://edpolicyinca.org/publications/covid-19-impacts-student-learning

Patrick, S. K., Woods, S. C., Bala, N., & Santelli, F. A. (2021). *Schooling during COVID-19: Fall semester trends from six Tennessee districts.* Tennessee Education Research Alliance.

Picciano, A. G., & Seaman, J. (2007). K–12 online learning: A survey of U.S. school district administrators. *Online Learning, 11*(3).

Randel, B., Swain, M., Norman Dvorak, R., Spratto, E., Prendez, J. Y. (2020). *Impact evaluation of mathematics i-Ready for striving learners using 2018-19: Final report.* Human Resources Research Organization (HumRRO).

Renaissance Learning. (2021). *How kids are performing: Tracking the midyear impact of COVID-19 on reading and mathematics achievement.* Renaissance Special Report Series, Winter 2020–2021 Edition. https://www.renaissance.com/howkids-are-performing/.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*, 169–188.

Sass. T. (2024). *Decentralization and the efficacy of intervention strategies to promote academic recovery*. Georgia Policy Labs.

Sass, T., & Goldring, T. (2021). *Student achievement growth during the COVID-19 pandemic.* Georgia Policy Labs. https://doi.org/10.57709/30728958.

Sass, T., & Goldring, T. (2022). *Student achievement growth during the COVID-19 pandemic: Fall 2021 update*. Georgia Policy Labs.

Sass, T., & Ali, S. M. (2022). *Student achievement growth during the COVID-19 pandemic: Spring 2022 update.* Georgia Policy Labs.

Sahni, S. D., Polanin, J. R., Zhang, Q., Michaelson, L. E., Caverly, S., Polese, M. L., & Yang, J. (2021). *A what works clearinghouse rapid evidence review of distance learning programs.* U.S. Department of Education.

Silver, D., Saavedra, A., & Polikoff, M. (2022). *Low parent interest in COVID-recovery interventions should worry educators and policymakers alike.* Brookings. Retrieved from https://www.brookings.edu/articles/low-parent-interest-in-covid-recovery-interventions-should-worry-educators-and-policymakers-alike/

Warschauer, M., & Matuchniak, T. (2010). New technology and digital worlds: Analyzing evidence of equity in access, use, and outcomes. *Review of Research in Education, 34*(1), 179–225.

What Works Clearinghouse (WWC). (2024). *WWC review of this study: Impact evaluation of reading "i-Ready" for striving learners using 2018–19 data. Final report. No. 053.* Institute of Education Sciences.

Wiburg, K., Chamberlin, B., Valdez, A., Trujillo, K., & Stanford, T. (2016). Impact of math snacks games on students' conceptual understanding. *Journal of Computers in Mathematics and Science Teaching, 35*(2), 173–193. https://eric.ed.gov/?id=EJ1095367

Wijekumar, K., Meyer, B. J., Lei, P. W., Lin, Y. C., Johnson, L. A., Spielvogel, J. A., Shurmatz, K. M., Ray, M., & Cook, M. (2014). Multisite randomized controlled trial examining intelligent tutoring of structure strategy for fifth-grade readers. *Journal of Research on Educational Effectiveness, 7*(4), 331–357. https://eric.ed.gov/?id=EJ1041354

Wijekumar, K., Meyer, B. J. F., & Lei, P. (2017). Web-based text structure strategy instruction improves seventh graders' content area reading comprehension. *Journal of Educational Psychology, 109*(6), 741–760. https://eric.ed.gov/?id=EJ1149967

Woo, Y., & Reeves, T. C. (2008). Interaction in asynchronous web-based learning environments: Strategies supported by educational research. *Online Learning*, *12*(3–4).

Woodworth, J. L., Raymond, M. E., Chirbas, K., Gonzalez, M., Negassi, Y., Snow, W., & Van Donge, C. (2015). Online charter school study 2015. *Center for Research on Educational Outcomes,* 1–104.

Zheng, L., Long, M., Zhong, L., & Gyasi, J. F. (2022). The effectiveness of technology-facilitated personalized learning on learning achievements and learning perceptions: A meta-analysis. *Education and Information Technologies, 27*(8), 11807–11830.