# Using Intensive Intervention to Improve Mathematics Skills of Students With Disabilities: Project Evaluation Report

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# Abstract

The purpose of this project evaluation was to assess the impact of data-based individualization (DBI) on the mathematics achievement of students with intensive mathematics learning needs, including students with disabilities. The evaluation study used a cluster randomized trial in which elementary schools were randomly assigned to treatment using a delayed-intervention design. Since this was a development project, the evaluation delineated between the primary, confirmatory impact question and exploratory research questions. The confirmatory question included students in Grades 1-2 and was concerned with the relationship of one year of DBI implementation support in comparison with a business-as-usual, delayed intervention group. Because of the developmental, iterative nature of the project, exploratory questions were concerned with cumulative longitudinal relations between years of DBI implementation support between two cohorts of elementary schools. In addition, project staff supported DBI implementation pilot in two middle schools and tracked student progress in those sites. Analytic results provided preliminary evidence to suggest that there may be contextual factors that govern the likelihood a student will profit from DBI. In addition, schools may require significant ongoing support to sustain implementation.

# Introduction

The purpose of the Investing in Innovation and Improvement (i3) development project, *Using Intensive Intervention to Improve Mathematics Skills of Students with Disabilities,* was to increase the achievement and skills of students with severe and persistent mathematics learning needs, including students with disabilities. This project was grounded in the concept of data-based individualization (DBI), an iterative and systematic approach to intensive intervention that uses student data to determine when and how to adapt, intensify, and individualize interventions for "high need" students who do not respond to more standardized methods (i.e., Tier 2 intervention) of remediation. For purposes of this project, high need students were identified by their lack of responsiveness to previous mathematics intervention or remediation efforts, disability status, or both.

DBI is a validated approach to intensive intervention that may be implemented as a component of a Multi-Tiered System of Supports (MTSS).[1] Its origins are in data-based program modification and experimental teaching (Deno & Mirkin, 1977). Prior randomized controlled trials (RCTs) and research syntheses have shown that the DBI process is associated with moderate-to-large effect sizes in literacy and mathematics (0.60 to 1.10; e.g., Jung, McMaster, Kunkel, Shin, & Stecker, 2018; Stecker, Fuchs, & Fuchs, 2005) when implemented in controlled settings. In addition, two meta-analyses of mathematics interventions for students with disabilities and low-performing students (Baker, Gersten, & Lee, 2002; Gersten et al., 2009) found that providing teachers with progress monitoring data and specific feedback on students' mathematics performance, which are critical components of DBI, appeared to have a positive impact on students' mathematics achievement.

The DBI process comprises five iterative steps (Peterson, Danielson, & Fuchs, 2019). Step one starts with the use of a validated intervention program or platform that is aligned with the student's area(s) of need (e.g., mathematics calculation, reading fluency). In step two, the teacher monitors progress using a valid, reliable assessment tool. If the student is making adequate progress, the intervention continues as designed. If progress is inadequate, however, the teacher collects additional diagnostic data to determine the student's instructional needs and hypothesize productive adaptations to the intervention program (step three). In step four, the teacher implements the adaptation(s), and continues to monitor progress to determine response (step 5). If the student is responsive, the intervention and progress monitoring continue to ensure ongoing progress. If response is inadequate, the teacher repeats steps 3–5, continuing to make data-based adaptations until the student demonstrates adequate progress.

Despite the body of evidence supporting the efficacy of DBI in controlled studies, many schools struggle to implement it, particularly in mathematics. Educators often note a number of reasons for this difficulty, including limited time for intervention in the school day, competing priorities, lack of qualified staff, and availability of validated intervention and progress monitoring tools. Bearing these issues in mind, this project attempted to implement DBI in the area of mathematics while *also* addressing the school and district-level challenges that often impede the implementation of evidence-based practices. In this project, we leveraged and extended the work of the National Center on Intensive Intervention (NCII; [www.intensiveintervention.org](http://www.intensiveintervention.org)), leaning

[1] We use the terms MTSS and Response to Intervention (RTI) interchangeably in this report.

on the lessons learned from previous DBI implementation efforts in schools and districts throughout the country.

Formative evaluation data from both NCII and the present project have shown that school teams can improve their implementation of DBI when they receive ongoing support (see Petscher, Margolin, Kuchle, Danielson, & Zumeta Edmonds, 2017; Schumacher, Zumeta Edmonds, & Arden, 2017). Thus, the primary mechanism for supporting educators to increase their capacity to deliver DBI to improve student-level outcomes in this project occurred through extensive collaboration with school intervention teams, local education agency (LEA) staff, and local coaches. The goal of this collaboration was to develop and implement comprehensive DBI systems in mathematics in eight elementary schools[2] in our partner district, located near Tacoma, Washington (See Appendix A: Project Logic Model). By extension, we also anticipated that our implementation support could have a secondary impact on overall implementation of MTSS in mathematics in these schools. Four project activities supported accomplishment of this goal, including:

- Conducting intake interviews that provided data about school readiness and baseline implementation of components of DBI and MTSS, and supported project planning.
- Providing structured support and training to develop and increase educators' knowledge and ability to implement DBI in mathematics.
- Soliciting feedback from families regarding their experience with DBI and special education processes through a series of interviews.
- Conducting formative and summative evaluation to plan project improvement and assess impact.

In the sections that follow, we describe the various components of our project, including implementation activities, the evaluation impact study that occurred during our first year of implementation[3] (2015–16), and findings from related exploratory analyses and evaluation activities (see also Appendix B). We conclude the report with a discussion of findings, limitations, and suggestions for future research.

# Research Questions

The purpose of our project evaluation was to assess the impact of DBI on the mathematics achievement of students with intensive mathematics learning needs, including students with disabilities. The evaluation study used a cluster RCT in which schools were randomly assigned to treatment using a delayed-intervention design. For purposes of this development grant, we delineated between the primary, confirmatory impact question and exploratory research questions. The confirmatory question included students in Grades 1–2 and was concerned with the relationship of one year of DBI implementation support in comparison with a business-as-usual, delayed intervention group. Because of the developmental, iterative nature of the project,

[2] At the request of our partner LEA, and with the approval of our project officer, we also supported implementation activities in the district's two middle schools from 2017 to 2019.
[3] This component of the report includes results of the NEi3 impact evaluation. The project's required fidelity assessment has been provided to the NEi3 team as a separate document.

the exploratory questions were concerned with cumulative longitudinal relations between years of DBI implementation support between two cohorts of elementary schools. The first cohort began receiving implementation support during the 2015–16 school year, and the second cohort received implementation support starting in the 2016–17 school year. For purposes of this evaluation, students were tracked over three school years, starting in Grades 1–2 through Grades 4–5, allowing for comparisons of students in the initial and delayed implementation cohorts. Mathematics achievement was the primary outcome domain, and multilevel models were used for analysis due to the hierarchical structure of the data, with students nested within schools.

The primary research question for the impact study was:

- What is the effect of one year of DBI (DBI Phase I) on mathematics achievement among Grades 1–2 students with severe and persistent mathematics learning needs[4] in treatment schools in comparison with business-as-usual instruction in control schools?

Exploratory research questions were:

- Do additional years of school implementation (i.e., dosage) of DBI yield higher mathematics achievement in elementary students with intensive mathematics learning needs, compared with schools with fewer years of implementation?
- Is there an interaction between intervention status and student characteristics (e.g., race, IEP status, achievement level)?
- What is the pattern of achievement observed in students in middle schools implementing DBI?[5]

# Method

## Participants

The project was conducted in a diverse, urban-adjacent public school district near Tacoma, Washington, within the district's eight elementary schools and two middle schools. At the commencement of the project, there were approximately 28 different languages spoken in the district, 9% of students were English learners (ELs), 72% of students received free or reduced-price lunch, and 12.3% were students with disabilities. Although project staff worked with school intervention teams throughout the project, we were interested in the impact of this work on student outcomes. Thus, student-level data were collected for purposes of the impact study. The sample consisted of approximately 4–5 Grade 1–2 students with intensive mathematics learning needs[6] in each elementary school ($n$ = 38) who were identified and tested over three school years (i.e., through Grades 4–5). In addition, we tracked a separate sample of middle school students ($n$ = 44) from Grade 6 to Grade 7 (i.e., two school years).

Students targeted to receive DBI were students with intensive mathematics learning needs, including those with disabilities. We considered a student to have intensive mathematics learning

[4] Including students with disabilities.
[5] Middle school implementation was not part of our initial evaluation plan, so this question was added.
[6] Including students with disabilities.

needs if he or she met one or more of the following conditions as defined by his or her teacher: (1) the student had an individualized education program (IEP), (2) the student demonstrated a lack of sufficient progress in a Tier II or other remedial intervention, and/or (3) the student was one of the lowest achieving students in his or her class based on school mathematics screening data.

## Measures

We collected data on three measures of student mathematics achievement, including *AIMSweb: Computation, AIMSweb: Concepts and Applications*, and the mathematics computation subtest of the *Wide Range Achievement Test–4* (WRAT). Measures were administered by experienced paraeducators who were trained to deliver the assessments. Assessments were scored, checked, and then entered into a database and checked for discrepancies to ensure accuracy.

*AIMSweb: Computation* (2010) is a general outcome measure that samples the annual curriculum to assess growth in mathematics calculations in Grades 1–8. Measures may be administered to individuals or groups and take approximately 8 minutes to complete. Construct validity ranges from .73–.84, and alternate form reliability ranges from .82–.90 across grades.

*AIMSweb: Concepts and Applications* (2009) is a general outcome measure that samples the annual curriculum to assess growth in mathematics concepts such as number concepts, geometry, and measurement, among others, in Grades 2–8. Measures may be administered to individuals or groups and take 8–10 minutes to complete. Predictive validity ranges from .60–.80, and alternate form reliability ranges from .80–.88 across grades.

The *WRAT–4* (Wilkinson & Roberston, 2006) mathematics computation subtest is an achievement measure that comprises two parts. Part 1 is a short, individually administered interview intended to assess basic number and counting concepts. It is typically administered to students age 7 years or younger and to older students who fail to achieve a minimum score on Part 2 of the assessment. Part 2 includes 40 mathematics calculations problems of increasing difficulty. Part 2 can be group administered and takes approximately 15 minutes to complete. Validity for the subtest was .85–.95 against the mathematics composite of the *Wechsler Individual Achievement Test–2* (2005), and coefficient alpha reliabilities were .87–.89 across parallel forms of the assessment.

## Project Activities

Project implementation was conducted in the district's eight elementary schools and two middle schools as depicted in Table 1. We summarize activities of each implementation year below.

### *DBI Phase I: Initial Implementation*

During DBI Phase I, intervention teams that included building principals, special educators, interventionists, and school psychologists began receiving implementation training and support. At the beginning of the school year, i3 project staff conducted site-based needs assessments to determine schools' baseline implementation of components of DBI and MTSS in mathematics and to determine specific support needs. Project staff used this information to plan and conduct monthly professional development and coaching sessions with teams from all Cohort 1 schools. Initially, content of the training sessions focused on building knowledge around the steps of the DBI implementation process. As teams began to familiarize themselves with DBI, project staff began to build in specific instructional content in mathematics, including a review of intervention programs that could be used as instructional platforms for implementing DBI. Professional development sessions addressed the following topics throughout the year:

- Introduction to DBI
- Using academic progress monitoring data to set goals, plan, and evaluate instruction
- Using diagnostic data to support instructional decision making
- Mathematics intervention platforms
- Adapting instruction to address counting and place value, basic facts, and fractions
- Planning effective student intervention meetings
- Reviewing student data and planning instruction
- Site-based implementation fidelity checks

Professional development sessions were followed up with implementation coaching sessions approximately once or twice monthly. These coaching sessions provided opportunities for intervention teams to refine processes, review data, integrate new learning, and begin student-level intervention planning, as appropriate.

*Waitlist Control (2015–16 only).* Cohort 2 school intervention teams did not participate in implementation activities during the 2015–16 school year and delivered mathematics instruction and intervention using business-as-usual procedures. Most students participated in a core grade-level mathematics program, but implementation of mathematics intervention was variable. Prior to the project, all schools in the district had access to screening and progress monitoring assessments, but schools' use of those measures also varied.

### *DBI Phase II: Ongoing Implementation*[7]

During DBI Phase II, project staff provided ongoing implementation and professional development throughout the school year. The scope and sequence of professional development reflected needs observed during the first year of implementation. School teams received refresher trainings on the DBI process, use of validated intervention platforms, intensification strategies, and the role of diagnostic data within the DBI process. Sites also participated in site visits from their project coach and project staff, which included a variety of activities such as observations of instruction, participation in data meetings, and reviews of professional development content. Additional monthly professional development activities also included a combination of school staff presentations on their progress toward implementing DBI with students and review of select

[7] Note that project activities in Implementation Years 2–4 were *not* a part of the impact study because Cohort 2 received the intervention during that time period. This practice was consistent with our approved evaluation plan.

DBI content. Project staff used a gradual release strategy to shift ownership of the DBI process to school staff in preparation for moving to DBI Phase III (Follow-Up).

### *DBI Phase III: Follow-Up*

During DBI Phase III, school teams did not receive regular monthly professional development and coaching from project staff. Instead, project staff focused on capacity and sustainability by providing coaching and implementation supports based on school team requests. These requests included support for data analysis at intervention meetings, assistance with the collection of diagnostic data, and support for integrating mathematics and behavior interventions. Cohort 1 schools also participated in an annual check of implementation fidelity in June of their follow-up year (2018) as a measure of sustained implementation during a time of minimal implementation supports.

*Middle School Implementation.* At the request of district leadership, project staff provided training to review the i3 priorities and DBI process with the district's MTSS team. Representatives across grade levels (K–12) constituting both special and general education attended this meeting. The objective of this review was to begin building a common language and process for providing intensive intervention to all students across the district. As a result, teams from the district's two middle school campuses expressed interest in instituting DBI at their sites. Project staff discussed this proposal with their i3 project officer and determined that it would be a beneficial opportunity for scaling up implementation within the district. Professional development materials were therefore modified for a middle school audience, and implementation topics followed a similar sequence as that described above for the elementary cohorts. Middle school implementation occurred during the 2017–18 and 2018–19 school years. Middle schools, however, were not part of the impact study.

## Evaluation Design

As noted, the effectiveness of the DBI implementation was evaluated in eight elementary schools[8] using a cluster RCT with a delayed-intervention design. Schools were the unit of randomization, which took place in August 2015. In order to optimize the randomization, the first step was to create four blocks of two schools each. The blocks were constructed based on the proportion of students eligible for free or reduced-price lunch, proportion of English language learners, school size, proportion of Black students, proportion of Hispanic students, and proportion of White students as variables for creating the blocks. Because of the known relations among these variables, principal component analysis was used to create a component score to explain the variance among the potential blocking variables. The component value is the linear combination from optimal weighting of the variables. The resulting component score for each school was used to sort schools from lowest to highest and created four blocks of two schools. Following these procedures, the block was used for random assignment via www.randomization.com to assign elementary schools within blocks to Cohort 1 or Cohort 2. Cohort 1 represented the immediate intervention group, while Cohort 2 represented the delayed

[8] The district's two middle schools were added as an additional cohort in 2017–18 at the request of our partner district and with permission from the grant's project officer. They were not involved in prior implementation years and so were not part of the impact study.

intervention group (waitlist control). As noted, the project implementation timeline is depicted in Table 1.

The comparison in 2015–16 between DBI Phase I in Cohort 1 and No DBI in Cohort 2 was the key confirmatory contrast of interest and was a true experimental contrast. The remaining between-cohort comparisons in Years 2 and 3 were exploratory and tested how dosage related to differences in outcomes. This is because the four schools assigned to the control group in 2015–16 began receiving DBI Phase I in the second year of the project (2016–17). Thus, statistical analyses for Year 2 and Year 3 data were comparisons of dosage between cohorts such that Year 2 was a comparison of two years of DBI in Cohort 1 compared with one year of DBI in Cohort 2. Similarly, Year 3 was a test of follow-up in Cohort 1 compared with two years of DBI in Cohort 2.

**Student selection.** Schools were the unit of random assignment, and to facilitate project buy in, we worked with school staff to identify students likely to profit from DBI for participation in the evaluation. Introductory training sessions were intended to allow school staff to accurately select students who were appropriate candidates for DBI; thus, eligible students were identified during December of 2015, and then tested in January 2016 (following school holidays and consent procedures). At the time of student selection, both Cohort 1 and Cohort 2 school staff were asked to use rosters from the time of randomization to select students who would be good candidates for DBI based on the criteria listed previously (i.e., students who had IEPs, or who had not been successful in a prior Tier II intervention, or who were among the lowest performing students in their grade based on school mathematics screening data). No students joined the sample after initial identification.

## Analysis

**Primary impact.** A multilevel model of students nested within schools was used to test the effect of one year of DBI implementation on Grades 1 and 2 outcomes. The primary impact model used was:

$$Y_{ij} = \gamma_{00} + \gamma_{01}(DBI_j) + \sum_{k=2}^{4} \gamma_{0k}(block_{(k)j}) + \gamma_{10}(pretest_{ij}) + \sum_{s=2}^{4} \gamma_{s0}(\text{student covariates}_{(s)ij}) + u_{0j} + r_{ij}$$

where $Y_{ij}$ is the mathematics score for student *i* in school *j*, $\text{DBI}_j$ is a dichotomous variable coded as 1 if school is a DBI school, and 0 otherwise, $\gamma_{00}$ is the estimated mean mathematics scores for comparison schools, $\gamma_{01}$ is the DBI (treatment) effect, $\gamma_{0k}$ represents the block effect, $\gamma_{10}$ is pretest fixed effect, and $\gamma_{s0}$ represents a set of selected student covariate fixed effects. Full information maximum likelihood was used to estimate fixed and random effects, and the Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) was applied to all statistically significant effects to guard against the false discovery rate. Following the test of main effects of DBI on the selected outcomes, three individual tests of moderation were conducted to evaluate the extent to which pretest, whether the student was on an IEP, or race differences moderated the relation between DBI and posttest performance. Statistically significant pairwise interactions at $p < .10$ were explored via simple slopes analysis to evaluate conditional differences and regions of significance.

**Exploratory analyses.** As a complementary approach to testing for main effects and interaction effects in a conditional means based multilevel model, a second set of exploratory analyses tested whether the impact of DBI was along levels of the conditional distribution of the mathematics achievement measures. The multilevel models used in the primary impact analysis are effective for empirically evaluating the *average* treatment effect; yet this approach based on averages may impose restrictions on interpretations. That is, most linear regression models are rooted in a conditional means approach that, by necessity, provides a conditional mean value of *y* (e.g., posttest) given a value of *x* (e.g., treatment). Although the mean is a desired property for estimating coefficients in a regression analysis, it is possible that associations between variables may vary depending on different points of the distribution of *y*. Quantile regression is a form of median regression that estimates the relations between *y* and *x* conditional on the distribution of *y* (Koenker & Bassett, 1978; Petscher & Logan, 2014). Where traditional linear regression is useful to answer the question, "What is the average relation between treatment and posttest scores?", quantile regression is useful to answer the question, "Does the relation between treatment and posttest scores vary depending on levels of the conditional posttest score?" Quantile regression has been applied under circumstances where a continuous outcome has been regressed on a dichotomous predictor. Thus, a natural extension of that model is to regress continuous posttest scores on a dummy-code variable of intervention effects. The estimated linear quantile mixed model to be used in this study was:

$$Y_{ij\tau} = \gamma_{00\tau} + \gamma_{01\tau}(DBI_j) + \sum_{k=2}^{4}\gamma_{0k\tau}(block_{(k)j}) + \gamma_{10\tau}(pretest_{ij}) + \sum_{s=2}^{4}\gamma_{s0\tau}(\text{student covariates}_{(s)ij}) + u_{0j\tau} + r_{ij\tau}$$

Where τ represents the quantile of the conditional distribution of the dependent variable. Just as in the conditional means model (i.e., the primary impact), intercept and slope coefficients, as well as random effects, are estimated in the quantile model; however, unlike the impact analysis, they are not estimated conditional on the mean but rather on other points of the conditional posttest distribution. Similar to the primary impact models, three separate interaction effects were also explored in quantile regressions for pretest, IEP, and race moderation.

Exploratory analyses also tested Year 2 and Year 3 impacts of DBI in Cohort 1 compared with lesser dosages of DBI in Cohort 2. That is, Year 1 provided data that conformed to a formal test of impacts in the RCT. Data from Year 2 allowed for a comparison of mathematics scores for those schools with two years of implementation compared with one year. Similarly, data from Year 3 afforded a comparison between schools that were in follow-up with those receiving a second year of DBI. Years 2 and 3 comparisons used the primary impact and interaction multilevel models for end-of-year comparisons.

Middle school data collected on students who began receiving DBI during project Year 3 were analyzed using a one-sample *t*-test. The absence of a comparison group necessarily precluded a between-group differences test; however, we opted to compare the middle school data to benchmark performance for moderate risk. Benchmarks for the fall, winter, and spring benchmarks for Grades 6 and 7 in *AIMSweb: Mathematics Computation* and *Mathematics Concepts and Applications* were used as the population value to which the sample mean was compared.

The lme4 package (Bates, Maechler, Bolker, & Walker, 2015) in R software was used for all primary impact models, and the lqmm package (Geraci, 2014) was used for the multilevel quantile models.

# Results

## Descriptive Statistics

Group-based means and standard deviations are reported in Table 2 for each of the measures used in the evaluation report. During Year 1 of implementation, the mean pretest for students in the DBI condition for *AIMSweb: Computation* was 11.09 (SD = 11.04) compared with 21.10 (SD = 13.77) for students in the comparison group. The standardized difference between groups was $g = 0.80$ and indicated that random assignment did not produce baseline equivalence on this outcome measure. The What Works Clearinghouse (WWC) has provided guidance that baseline equivalence is empirically supported when absolute difference in effect sizes are <= 0.05. When the absolute baseline effect size value is calculated up to 0.25, one may use a covariate adjusted score (e.g., the primary impact model previously described); however, when the absolute effect size exceeds 0.25, the data do not satisfy criteria for baseline equivalence (U.S. Department of Education, Institute of Education Sciences, 2019). As such, one of two options presented for our study: (1) attempt to create a quasi-experimental analytic sample using propensity score matching, or (2) opt not to analyze the data. Due to the small, balanced analytic sample, propensity score matching was less plausible in terms of producing equivalent groups; thus, we opted not to use the mathematics computation outcome for evaluation purposes.

The *AIMSweb: Concepts and Applications* assessment was administered to Grade 2 students. Students in the DBI condition had a mean score of 5.14 (SD = 4.33) compared with 4.94 (SD = 4.07) for the comparison students. The standardized effect size of $g = 0.05$ met the WWC guidelines for baseline equivalence. Similarly, the WRAT baseline assessments met baseline equivalence metrics for the total score ($g = -0.30$), the Part 1 score ($g = -0.09$), and the Part 2 score ($g = -0.14$). For each of these outcomes, the primary impact and exploratory models were estimated.

## Year 1 Impact Results

Table 3 reports findings from the primary impact and moderation models for Grade 2 *AIMSweb: Concepts and Applications*. No statistically significant effect of DBI was observed in the impact model (-0.53, $p = .703$). Further, no significant interaction was estimated for baseline moderation (-0.15, $p = .589$), IEP moderation (0.82, $p = .716$), or race moderation (-1.13, $p = .216$). No main effects were observed on the WRAT total score (0.32, $p = .685$; Table 4), nor were there significant interactions; however, significant interactions were observed for baseline moderation on Part 1 of the WRAT score (0.32, $p = .051$; Table 5) and on Part 2 of the WRAT score (-0.58, $p = .021$; Table 6). A simple slopes analysis (Table 29) looked at the regions of significance at levels of one standard deviation above (1SD) and below (-1SD) the mean as well as at the mean across levels of DBI and comparison groups. Based on these pretest regions, there were no significant differences between DBI and comparison at -1SD (-0.55, $p = .357$), the mean (0.16, $p = .740$), or 1SD (0.87, $p = .161$) for WRAT Part 1 in Year 1. When considering the simple slopes of WRAT Part 2 in Year 1 (Table 29), there were no significant differences between DBI and comparison at -1SD (1.07, $p$ =.055)[9] and the mean (-0.08, $p$ = .861), but there were significant differences at 1SD in favor of the comparison group (-1.23, $p$ =.033).

The majority of DBI coefficients and interactions were not statistically significant, but the multilevel quantile results (Tables 7–22) yielded several important findings. The pretest moderation model for the WRAT total score (Table 12) showed significant interactions at the .50 quantile (-0.73, $p$ = .028) and the .75 quantile (-0.96, $p$ = .010) of the WRAT, suggesting that the impact of pretest WRAT on the relation between DBI and posttest was stronger at higher conditional quantiles of the WRAT total score. Baseline moderation was also significant for Part 1 of the WRAT at the .25 quantile (0.46, $p$ = .021) and the .50 quantile (0.31, $p$ = .082), suggesting that the impact of moderation was stronger at lower conditionals quantiles of the WRAT Part 1 (Table 16). Table 18 shows a significant interaction for DBI by race at the .75 quantile (-0.40, $p$ < .10), and Table 20 shows a significant interaction for DBI by pretest at the .75 quantile (-0.54, $p$ = .087).

## Year 2 Cohort Comparisons

Results for Year 2 comparisons between Cohort 1 (i.e., two years of DBI implementation) and Cohort 2 (i.e., one year of DBI implementation) on *AIMSweb: Concepts and Applications* are reported in Table 23. Results showed no significant effect in the primary impact model (2.39, $p$ = .196); no significant interactions were observed as well.

## Year 3 Cohort Comparisons

A significant interaction was estimated in the Year 3 comparison for DBI by race (-9.75, $p$ = .006; Table 24) for *Aims Web: Concepts and Applications.* Simple slopes analysis (Table 28) showed that non-White students in Cohort 1 schools statistically outperformed non-White students in Cohort 2 schools (4.27, $p$ = .018). Conversely, there was no difference in scores for White students between Cohorts (-5.48, $p$ = .072). A significant interaction between DBI and baseline was observed for the WRAT total (Table 25) with results indicating that Cohort 1 students with -1SD baseline scores did score as well as Cohort 2 students (-3.02, $p$ = .004; Table 28) and no differences between cohorts for those at the mean (-1.42, $p$ = .060) or 1SD (0.18, $p$ = .872). A significant interaction for baseline was estimated on the WRAT Part 1 (0.37, $p$ < .001; Table 26) with simple slopes analysis showing that Cohort 1 students performed lower than Cohort 2 students at -1SD of baseline (-1.13, $p$ < .001), but no differences were noted between cohorts at the mean (-0.34, $p$ = .144) or 1SD (0.45, $p$ = .169). No significant interactions were noted for WRAT Part 2 (Table 27).

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[9] Although the conditional values for the simple slope analysis used one standard deviation thresholds, we opted to do a secondary test given the result of the WRAT Part 2 hypothesis test. When using a 1.25 SD threshold value, the DBI students who were -1.25 SD on baseline statistically out-performed individuals who did not receive DBI (1.35, $p$ = .038). As well, students who were 1.25 SD above the mean on baseline and received DBI performed lower on the post-test compared to those who did not receive DBI (-1.52, $p$ = *.026).*

### Middle School Findings

Results from the one sample *t*-test for middle school students are reported in Table 28. The mean scores for the *AIMSweb: Computation* subtest tended to show increases from fall to winter and decreases from winter to spring. Across the six time points, only one test was statistically significant (i.e., Grade 6, winter; $p$ = .048), suggesting that students' mean performance was above the benchmark threshold. No significant differences were observed for the *AIMSweb: Concepts and Applications* assessment.

## Discussion

Our results suggest that contextual factors may govern the likelihood that a student will be successful in DBI. With respect to the primary impact research question, results revealed no significant main effects for condition. In addition, the lack of pretreatment equivalence on the *AIMSweb: Computation* limited our ability to compare the two groups on that measure. At the same time, findings from exploratory analyses revealed interesting results that may warrant further investigation. Given the small sample and developmental nature of this project, all findings should be interpreted with caution and would benefit from further controlled study.

First, findings from the Year 1 WRAT Part 2 analyses suggest a potential small positive effect of DBI for students performing well below the mean and a positive effect for the comparison group for students performing 1SD above the mean. Although we did not observe a significant effect at 1SD below the mean, the effect was reliable in favor of DBI for students performing 1.25 SD below. These trends may have implications for identifying students likely to benefit from DBI versus those who may benefit from less intensive levels of support. Given the low power and developmental nature of these data, we believe these findings are noteworthy and could benefit from replication with a larger sample. In particular, future research could investigate potential approaches to determining screening cut points to identify students with immediate need for DBI. In addition, it may be useful to determine the extent to which gated screening procedures or dynamic assessments such as those described by Fuchs, Fuchs, and Compton (2012) may help to improve timely, accurate identification of students.

Given the differential impacts of DBI on higher and lower achieving students observed, it may also be useful to further investigate the extent to which interventions are appropriately intensive and aligned with students' needs. Throughout the project, teachers reported lack of alignment between core instruction and intervention materials. We investigated this issue and confirmed poor alignment related to both mathematics instructional practices and vocabulary in three commonly used programs in our partner district. (See Appendix B and Nelson, Pfannenstiel, & Zumeta Edmonds, 2020, for more information.) Thus, we believe future efforts to implement DBI in mathematics may benefit from more intentional planning to ensure that core instruction and intervention efforts complement one another.

Another finding of interest was the positive effect of the third year of DBI observed for non-White students on *AIMSweb: Concepts and Applications* (a proximal outcome measure) in Cohort 1. This finding suggests that there may be an additive positive effect of intervention over time for non-white students. Due to low statistical power, ELs were not analyzed separately in this sample, so it is also possible that EL status and race were conflated. Thus, it may be useful to also investigate the interaction between EL status and DBI in future work.

We also observed that lower achieving students (-1SD below the mean) in Cohort 1 performed *at lower levels* than Cohort 2 students on the *WRAT* in Year 3. Keeping in mind the quasi-experimental nature of these data compared with the experimental data from Year 1, it should be noted that Year 3 was a follow-up year for Cohort 1 schools, meaning that these schools did not receive regular implementation supports during that time period. Anecdotally, we also observed a decline in implementation fidelity in some of our Cohort 1 schools during our annual implementation checks that year. (See Appendix B for a description of these implementation checks.) In addition, turnover of several critical district leaders during this time period may have further undermined efforts to sustain implementation. Thus, it is possible that these results suggest a need for schools to receive ongoing support and clear district-level policies to help sustain implementation of DBI.

Finally, our middle school findings were limited by the lack of control condition and the fact that we monitored students at their chronological grade levels rather than their instructional levels. This issue may have been particularly problematic for older students whose performance is often several years below grade level, making it difficult for the measures to detect change. Furthermore, we observed that many middle school teachers tended to assume that students had mastered skills that many had not, and they were often hesitant to reteach foundational skills. Many teachers also struggled to use student-level data to inform intensification and adaptation of intervention because they felt tied to delivery of their core curriculum and pacing guide, which made it difficult for them to adapt instruction. Future work at the middle school level should attempt to address these implementation challenges and should track students at their instructional levels to increase the likelihood of detecting progress if it occurs.

## Limitations

Although we observed some potentially interesting findings, we believe they should be considered in light of several important limitations. First, the developmental nature of the project meant that we worked with a small number of schools and tracked a small sample of students. Consequently, statistical power was low. Furthermore, our partner district serves a very transient student population and, as a result, attrition was high throughout the project. Attrition among elementary students was approximately 50% over three years and was nearly 30% over two years for middle school students. Therefore, our findings must be interpreted with caution, and future attempts to replicate or extend this work should include larger samples to enhance power and help control for attrition.

Furthermore, although schools were blocked and randomly assigned to conditions, our project fidelity data suggested that some Cohort 2 schools appeared to enter the project with higher baseline implementation of elements of MTSS and DBI-related processes. This may have impacted their uptake of the intervention in Years 2 and 3 and could be indicative of critical differences in leadership and management in these schools. Given that each cohort had only four elementary schools, these differences may have biased some findings in favor of the control group.

In addition, while our efforts to monitor implementation fidelity (see Appendix B) allowed us to look at systemic features of implementation, we were not able to assess the extent to which DBI was implemented with fidelity at the individual student level. In other words, although schools may have made promising changes to their systems (e.g., time allocated for mathematics intervention, adoption of evidence-based intervention platforms), the extent to which DBI procedures (e.g., delivering intervention aligned to student needs, implementing timely instructional changes based on data) were actually applied to specific students remains unclear. Given this and the variation in outcomes we observed across students, we believe future efforts to assess fidelity should include a more systematic evaluation of student-level implementation. Furthermore, future efforts to evaluate DBI should be sufficiently powered to allow measures of implementation fidelity to be included as a covariate in analytic models.

# Conclusion

Findings from our project evaluation suggest that the impact of DBI may be differential and localized based on student characteristics such as prior achievement level and race. Our findings point to a need for screening procedures to identify students likely to benefit from DBI and for more robust procedures to ensure that individual students receive intensive interventions that are appropriately aligned to their needs. Furthermore, we suspect that schools may require additional sustained support to maintain implementation over time. Given the critical need to continue to improve outcomes for students with intensive learning needs, we hope this project has helped to lay the groundwork for productive future lines of research to address these ongoing questions.

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**Table 1. Project Implementation Timeline**

| Implementation School Year | Implementation Phase |
|---|---|
| 2015–16[a] | Cohort 1[b]: DBI Phase I<br>Cohort 2: Waitlist control/ No DBI |
| 2016–17 | Cohort 1: DBI Phase II<br>Cohort 2: DBI Phase I |
| 2017–18 | Cohort 1: DBI Phase III (Follow-Up)<br>Cohort 2: DBI Phase II<br>Middle School Cohort: DBI Phase I |
| 2018–19 | Cohort 2: DBI Phase III (Follow-Up)<br>Middle School Cohort: DBI Phase II |

[a] This was the NEi3 impact study year.
[b] Cohorts 1 and 2 comprised four elementary schools, respectively.

**Table 2. Descriptive Statistics by Group and Measure**

| Contrast | Measure | Year | Administration | DBI | | | Comparison | | | Hedges *g* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *N* | Mean | SD | *N* | Mean | SD | |
| Combined Grades 1–2 | Mathematics Computation | 1 | Fall | 34 | 11.09 | 11.04 | 30 | 21.10 | 13.77 | 0.80 |
| | | | Spring | - | - | - | - | - | - | - |
| Grade 2 | Mathematics CAP | 1 | Fall | 21 | 5.14 | 4.33 | 17 | 4.94 | 4.07 | 0.05 |
| | | | Spring | 21 | 7.35 | 4.82 | 17 | 8.00 | 5.33 | -0.13 |
| | | 2 | Spring | 21 | 9.62 | 5.97 | 17 | 7.00 | 5.60 | 0.45 |
| | | 3 | Winter | 21 | 7.10 | 5.53 | 17 | 5.71 | 5.72 | 0.25 |
| Combined Grades 1–2 | WRAT Total | 1 | Pretest | 28 | 16.20 | 3.88 | 25 | 16.30 | 4.00 | -0.03 |
| | | | Posttest | 28 | 18.50 | 4.76 | 25 | 18.51 | 4.83 | -0.001 |
| | | 3 | Follow-up | 21 | 23.00 | 4.98 | 16 | 23.90 | 3.07 | -0.21 |
| Combined Grades 1–2 | WRAT Part 1 | 1 | Pretest | 34 | 12.2 | 2.19 | 31 | 12.4 | 2.13 | -0.09 |
| | | | Posttest | 34 | 13.10 | 2.24 | 31 | 13.20 | 1.59 | -0.05 |
| | | 3 | Follow-up | 21 | 14.50 | 1.12 | 16 | 15.00 | 0.00 | -0.63 |
| Combined Grades 1–2 | WRAT Part 2 | 1 | Pretest | 34 | 4.06 | 2.04 | 31 | 3.77 | 2.01 | 0.14 |
| | | | Posttest | 34 | 5.39 | 3.48 | 31 | 5.23 | 3.05 | 0.05 |
| | | 3 | Follow-up | 21 | 8.52 | 4.15 | 16 | 8.88 | 3.07 | -0.10 |

**Table 3. Impact and Moderation Models for Grade 2 Mathematics Concepts and Applications**

| | Impact | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** |
| (Intercept) | 7.05 | 1.97 | <0.001 | 7.07 | 1.99 | <0.001 | 8.64 | 2.67 | 0.001 | 5.01 | 3.53 | 0.156 |
| Pretest | 0.83 | 0.14 | <0.001 | 0.91 | 0.21 | <0.001 | 0.72 | 0.15 | <0.001 | 0.91 | 0.16 | <0.001 |
| DBI | -0.53 | 1.40 | 0.703 | -0.56 | 1.41 | 0.693 | -1.22 | 2.27 | 0.591 | 2.75 | 3.16 | 0.385 |
| Block | 0.32 | 0.65 | 0.618 | 0.32 | 0.66 | 0.624 | 0.33 | 0.82 | 0.686 | 0.71 | 0.88 | 0.419 |
| DBI*Pretest | | | | -0.15 | 0.27 | 0.589 | | | | | | |
| IEP | | | | | | | -2.59 | 1.74 | 0.136 | | | |
| DBI*IEP | | | | | | | 0.82 | 2.25 | 0.716 | | | |
| Race | | | | | | | | | | 0.34 | 0.57 | 0.557 |
| DBI*Race | | | | | | | | | | -1.13 | 0.91 | 0.216 |
| **Random Effects** | | | | | | | | | | | | |
| σ2 | 10.38 | | | 10.22 | | | 10.19 | | | 11.02 | | |
| $\tau_{00}$ | 1.51 School | | | 1.63 School | | | 3.99 School | | | 3.22 School | | |
| ICC | 0.13 | | | 0.14 | | | 0.28 | | | 0.23 | | |

**Table 4. Impact and Moderation Models for WRAT Total Score**

| | Impact | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** |
| (Intercept) | 16.99 | 1.51 | <0.001 | 17.00 | 1.41 | <0.001 | 16.78 | 1.38 | <0.001 | 17.90 | 2.38 | <0.001 |
| Block | -0.31 | 0.36 | 0.394 | -0.30 | 0.31 | 0.347 | -0.21 | 0.31 | 0.498 | -0.43 | 0.46 | 0.352 |
| Pretest | 0.92 | 0.10 | <0.001 | 1.05 | 0.14 | <0.001 | 0.86 | 0.10 | <0.001 | 0.92 | 0.11 | <0.001 |
| Grade | 1.44 | 0.73 | 0.048 | 1.43 | 0.72 | 0.049 | 2.04 | 0.76 | 0.007 | 1.39 | 0.75 | 0.065 |
| DBI | 0.32 | 0.79 | 0.685 | 0.27 | 0.68 | 0.694 | -0.05 | 0.92 | 0.954 | -0.32 | 1.71 | 0.853 |
| DBI*Pretest | | | | -0.19 | 0.17 | 0.260 | | | | | | |
| DBI*IEP | | | | | | | 0.34 | 1.27 | 0.790 | | | |
| IEP | | | | | | | -1.70 | 0.99 | 0.085 | | | |
| DBI*Race | | | | | | | | | | 0.22 | 0.53 | 0.675 |
| Race | | | | | | | | | | -0.18 | 0.35 | 0.605 |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 5.07 | | | 5.22 | | | 4.97 | | | 5.21 | | |
| $\tau_{00}$ | 0.45 School | | | 0.11 School | | | 0.09 School | | | 0.61 School | | |
| ICC | 0.08 | | | 0.02 | | | 0.02 | | | 0.10 | | |

**Table 5. Impact and Moderation Models for WRAT Part 1 Score**

| Predictors | Impact | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* |
| (Intercept) | 11.55 | 0.77 | <0.001 | 11.50 | 0.86 | <0.001 | 11.52 | 0.78 | <0.001 | 10.86 | 1.21 | <0.001 |
| Block | 0.01 | 0.16 | 0.956 | -0.04 | 0.22 | 0.863 | 0.05 | 0.17 | 0.789 | 0.07 | 0.21 | 0.730 |
| Pretest | 0.55 | 0.09 | <0.001 | 0.33 | 0.13 | 0.011 | 0.52 | 0.10 | <0.001 | 0.53 | 0.10 | <0.001 |
| Grade | 1.05 | 0.40 | 0.008 | 1.15 | 0.39 | 0.003 | 1.22 | 0.42 | 0.004 | 1.13 | 0.41 | 0.006 |
| DBI | 0.09 | 0.36 | 0.801 | 0.16 | 0.47 | 0.734 | -0.09 | 0.52 | 0.865 | 0.42 | 0.85 | 0.621 |
| DBI*Pretest | | | | 0.32 | 0.17 | **0.051** | | | | | | |
| DBI*IEP | | | | | | | 0.25 | 0.73 | 0.734 | | | |
| IEP | | | | | | | -0.60 | 0.56 | 0.284 | | | |
| DBI*Race | | | | | | | | | | -0.11 | 0.28 | 0.693 |
| Race | | | | | | | | | | 0.14 | 0.17 | 0.416 |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 1.65 | | | 1.48 | | | 1.67 | | | 1.69 | | |
| $\tau_{00}$ | 0.00 School | | | 0.22 School | | | 0.00 School | | | 0.00 School | | |
| ICC | | | | 0.13 | | | | | | | | |

**Table 6. Impact and Moderation Models for WRAT Part 2 Score**

| *Predictors* | Impact | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* |
| (Intercept) | 5.44 | 1.18 | <0.001 | 5.64 | 1.13 | <0.001 | 5.14 | 1.09 | <0.001 | 6.96 | 1.67 | <0.001 |
| Block | -0.37 | 0.29 | 0.201 | -0.44 | 0.28 | 0.108 | -0.31 | 0.25 | 0.217 | -0.58 | 0.32 | 0.070 |
| Pretest | 1.18 | 0.15 | <0.001 | 1.51 | 0.20 | <0.001 | 1.07 | 0.15 | <0.001 | 1.18 | 0.15 | <0.001 |
| Grade | 0.55 | 0.57 | 0.331 | 0.57 | 0.54 | 0.289 | 1.04 | 0.60 | 0.082 | 0.47 | 0.57 | 0.414 |
| DBI | -0.02 | 0.62 | 0.968 | -0.09 | 0.59 | 0.879 | -0.06 | 0.74 | 0.934 | -1.29 | 1.21 | 0.289 |
| DBI*Pretest | | | | -0.58 | 0.25 | **0.021** | | | | | | |
| DBI*IEP | | | | | | | -0.14 | 1.00 | 0.892 | | | |
| IEP | | | | | | | -1.11 | 0.78 | 0.158 | | | |
| DBI*Race | | | | | | | | | | 0.45 | 0.39 | 0.253 |
| Race | | | | | | | | | | -0.30 | 0.25 | 0.233 |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 3.20 | | | 2.95 | | | 3.12 | | | 3.29 | | |
| $\tau_{00}$ | 0.29 School | | | 0.26 School | | | 0.11 School | | | 0.17 School | | |
| ICC | 0.08 | | | 0.08 | | | 0.03 | | | 0.05 | | |

**Table 7. Multilevel Quantile Impact Model for Grade 2 Mathematics Concepts and Applications**

| Quantile | Parameter | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|
| 0.25 | Intercept | 2.33 | 0.05 | 9.42 | 0.048 |
| | Block | 0.94 | -1.41 | 2.35 | 0.616 |
| | Pretest | 0.1 | 0.43 | 0.85 | 0.000 |
| | DBI | 1.66 | -3.87 | 2.79 | 0.745 |
| 0.5 | Intercept | 2.89 | -1.19 | 10.45 | 0.116 |
| | Block | 1.26 | -1.97 | 3.11 | 0.656 |
| | Pretest | 0.23 | 0.17 | 1.1 | 0.008 |
| | DBI | 1.77 | -3.72 | 3.39 | 0.925 |
| 0.75 | Intercept | 3.73 | 3.64 | 18.65 | 0.004 |
| | Block | 1.55 | -3.6 | 2.62 | 0.752 |
| | Pretest | 0.39 | 0.39 | 1.98 | 0.004 |
| | DBI | 2.64 | -4.99 | 5.63 | 0.904 |

**Table 8. Multilevel Quantile Baseline Moderation Model for Grade 2 Mathematics Concepts and Applications**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 5.18 | 1.82 | 1.52 | 8.85 | 0.006 |
| | Block | 0.31 | 0.87 | -1.43 | 2.05 | 0.724 |
| | Pretest | 0.62 | 0.12 | 0.39 | 0.86 | 0.000 |
| | DBI | -2.39 | 1.78 | -5.97 | 1.20 | 0.187 |
| | Pretest*DBI | -0.08 | 0.49 | -1.06 | 0.89 | 0.863 |
| 0.5 | Intercept | 5.94 | 2.22 | 1.48 | 10.39 | 0.010 |
| | Block | 0.26 | 1.02 | -1.78 | 2.31 | 0.796 |
| | Pretest | 0.81 | 0.26 | 0.28 | 1.34 | 0.003 |
| | DBI | 0.42 | 1.94 | -3.48 | 4.32 | 0.829 |
| | Pretest*DBI | -0.18 | 0.63 | -1.45 | 1.08 | 0.771 |
| 0.75 | Intercept | 8.68 | 3.10 | 2.45 | 14.90 | 0.007 |
| | Block | 0.34 | 1.20 | -2.08 | 2.76 | 0.776 |
| | Pretest | 1.29 | 0.41 | 0.46 | 2.12 | 0.003 |
| | DBI | -0.25 | 2.80 | -5.86 | 5.37 | 0.930 |
| | Pretest*DBI | -0.21 | 0.84 | -1.89 | 1.47 | 0.802 |

**Table 9. Multilevel Quantile IEP Moderation Model for Grade 2 Mathematics Concepts and Applications**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 8.19 | 3.76 | 0.64 | 15.74 | 0.034 |
| | Block | -0.19 | 1.27 | -2.73 | 2.36 | 0.884 |
| | Pretest | 0.60 | 0.16 | 0.28 | 0.92 | 0.000 |
| | DBI | -1.18 | 3.04 | -7.28 | 4.92 | 0.699 |
| | IEP | -2.61 | 1.85 | -6.33 | 1.12 | 0.166 |
| | IEP*DBI | 1.01 | 2.25 | -3.52 | 5.53 | 0.657 |
| 0.50 | Intercept | 7.55 | 4.56 | -1.61 | 16.72 | 0.104 |
| | Block | 0.37 | 1.53 | -2.71 | 3.44 | 0.812 |
| | Pretest | 0.62 | 0.34 | -0.06 | 1.29 | 0.074 |
| | DBI | -1.54 | 4.38 | -10.34 | 7.25 | 0.726 |
| | IEP | -2.08 | 2.49 | -7.08 | 2.92 | 0.407 |
| | IEP*DBI | 0.47 | 3.56 | -6.68 | 7.62 | 0.896 |
| 0.75 | Intercept | 11.17 | 4.66 | 1.80 | 20.54 | 0.020 |
| | Block | 0.73 | 1.63 | -2.54 | 4.00 | 0.654 |
| | Pretest | 1.26 | 0.35 | 0.54 | 1.97 | 0.001 |
| | DBI | -1.89 | 4.49 | -10.92 | 7.14 | 0.676 |
| | IEP | -4.69 | 3.04 | -10.79 | 1.42 | 0.129 |
| | IEP*DBI | 2.43 | 3.80 | -5.21 | 10.06 | 0.526 |

**Table 10. Multilevel Quantile Race Moderation Model for Grade 2 Mathematics Concepts and Applications**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 3.43 | 4.95 | -6.52 | 13.38 | 0.492 |
| | Block | 0.61 | 1.46 | -2.33 | 3.54 | 0.680 |
| | Pretest | 0.65 | 0.12 | 0.41 | 0.90 | 0.000 |
| | DBI | 3.65 | 3.26 | -2.91 | 10.21 | 0.269 |
| | Race | 0.21 | 0.59 | -0.97 | 1.39 | 0.723 |
| | Race*DBI | -1.31 | 0.88 | -3.09 | 0.46 | 0.144 |
| 0.50 | Intercept | 3.52 | 4.50 | -5.52 | 12.57 | 0.437 |
| | Block | 1.16 | 1.48 | -1.81 | 4.13 | 0.436 |
| | Pretest | 0.92 | 0.28 | 0.36 | 1.48 | 0.002 |
| | DBI | 4.24 | 3.32 | -2.43 | 10.92 | 0.207 |
| | Race | 0.26 | 0.61 | -0.96 | 1.48 | 0.672 |
| | Race*DBI | -1.59 | 1.05 | -3.71 | 0.53 | 0.138 |
| 0.75 | Intercept | 5.38 | 4.90 | -4.48 | 15.23 | 0.278 |
| | Block | 0.92 | 1.70 | -2.50 | 4.34 | 0.590 |
| | Pretest | 1.29 | 0.39 | 0.51 | 2.06 | 0.002 |
| | DBI | 4.74 | 3.62 | -2.53 | 12.01 | 0.197 |
| | Race | 0.71 | 0.73 | -0.75 | 2.17 | 0.332 |
| | Race*DBI | -2.18 | 1.70 | -5.60 | 1.23 | 0.204 |

**Table 11. Multilevel Quantile Impact Model for WRAT Total Score**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 15.69 | 3.21 | 9.24 | 22.14 | 0.000 |
| | Block | -0.56 | 0.64 | -1.85 | 0.74 | 0.390 |
| | Pretest | 1.78 | 0.24 | 1.30 | 2.25 | 0.000 |
| | DBI | -0.56 | 1.75 | -4.06 | 2.95 | 0.751 |
| 0.50 | Intercept | 16.73 | 3.64 | 9.41 | 24.05 | 0.000 |
| | Block | -0.49 | 0.66 | -1.81 | 0.83 | 0.458 |
| | Pretest | 1.67 | 0.28 | 1.11 | 2.23 | 0.000 |
| | DBI | 0.35 | 1.42 | -2.51 | 3.21 | 0.807 |
| 0.75 | Intercept | 17.86 | 2.08 | 13.68 | 22.04 | 0.000 |
| | Block | -0.25 | 0.56 | -1.38 | 0.88 | 0.658 |
| | Pretest | 1.75 | 0.34 | 1.07 | 2.43 | 0.000 |
| | DBI | 0.50 | 1.16 | -1.82 | 2.82 | 0.667 |

**Table 12. Multilevel Quantile Baseline Moderation Model for WRAT Total Score**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 15.66 | 3.47 | 8.67 | 22.64 | 0.000 |
| | Block | -0.65 | 0.61 | -1.87 | 0.58 | 0.292 |
| | Pretest | 1.82 | 0.35 | 1.12 | 2.53 | 0.000 |
| | DBI | -0.79 | 1.27 | -3.34 | 1.76 | 0.535 |
| | Pretest*DBI | -0.16 | 0.51 | -1.17 | 0.86 | 0.759 |
| 0.5 | Intercept | 17.03 | 3.36 | 10.29 | 23.78 | 0.000 |
| | Block | -0.61 | 0.63 | -1.88 | 0.66 | 0.341 |
| | Pretest | 2.11 | 0.33 | 1.44 | 2.78 | 0.000 |
| | DBI | 0.26 | 1.22 | -2.19 | 2.70 | 0.833 |
| | Pretest*DBI | -0.73 | 0.32 | -1.37 | -0.08 | **0.028** |
| 0.75 | Intercept | 18.15 | 2.02 | 14.09 | 22.20 | 0.000 |
| | Block | -0.34 | 0.47 | -1.28 | 0.60 | 0.467 |
| | Pretest | 2.32 | 0.33 | 1.66 | 2.98 | 0.000 |
| | DBI | 0.42 | 0.84 | -1.27 | 2.11 | 0.620 |
| | Pretest*DBI | -0.96 | 0.36 | -1.67 | -0.24 | **0.010** |

**Table 13. Quantile IEP Moderation Model for WRAT Total Score**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| (Intercept) | 18.87** (2.18) | 19.84** (1.33) | 20.84** (0.96) |
| Block | -1.00* (0.45) | 0.00 (0.43) | 0.00 (0.26) |
| Pretest | 1.67** (0.19) | 2.00** (0.27) | 2.00** (0.14) |
| DBI | 1.00 (2.20) | 0.00 (1.71) | 1.00 (0.75) |
| IEP | 0.67 (1.91) | -1.00 (1.34) | -1.00 (0.78) |
| DBI*IEP | -1.00 (2.45) | -1.00 (2.01) | -1.00 (1.33) |
| Quantile | 0.25 | 0.50 | 0.75 |

$^{**}p < 0.001$, $^{*}p < 0.05$,

**Table 14. Quantile Race Moderation Model for WRAT Total Score**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| (Intercept) | 16.86* (2.46) | 22.00* (2.52) | 20.83* (1.26) |
| Block | -0.50 (0.57) | -0.89 (0.59) | -0.21 (0.37) |
| Pretest | 1.75* (0.22) | 2.00* (0.25) | 2.12* (0.17) |
| DBI | 1.00 (2.58) | -1.71 (2.18) | -0.18 (1.40) |
| Race | 0.38 (0.37) | -0.38 (0.36) | -0.14 (0.19) |
| DBI*Race | -0.25 (0.71) | 0.60 (0.73) | 0.41 (0.55) |
| Quantile | 0.25 | 0.50 | 0.75 |

*$p < 0.001$

**Table 15. Multilevel Quantile Impact Model for WRAT Part 1**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 10.24 | 2.04 | 6.13 | 14.34 | 0.000 |
| | Block | -0.24 | 0.61 | -1.46 | 0.99 | 0.701 |
| | Pretest | 0.48 | 0.18 | 0.11 | 0.84 | 0.011 |
| | DBI | -0.19 | 0.84 | -1.86 | 1.49 | 0.824 |
| 0.5 | Intercept | 11.96 | 1.18 | 9.58 | 14.34 | 0.000 |
| | Block | -0.25 | 0.18 | -0.62 | 0.12 | 0.182 |
| | Pretest | 0.50 | 0.17 | 0.16 | 0.84 | 0.004 |
| | DBI | 0.00 | 0.50 | -1.01 | 1.01 | 1.000 |
| 0.75 | Intercept | 12.42 | 1.12 | 10.17 | 14.68 | 0.000 |
| | Block | 0.00 | 0.25 | -0.51 | 0.51 | 1.000 |
| | Pretest | 0.49 | 0.23 | 0.03 | 0.95 | 0.036 |
| | DBI | 0.01 | 0.57 | -1.13 | 1.15 | 0.980 |

**Table 16. Multilevel Quantile Baseline Moderation Model for WRAT Part 1**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 12.59 | 1.80 | 8.98 | 16.19 | 0.000 |
| | Block | 0.00 | 0.61 | -1.22 | 1.22 | 1.000 |
| | Pretest | 0.54 | 0.17 | 0.21 | 0.88 | 0.002 |
| | DBI | 0.33 | 1.07 | -1.81 | 2.48 | 0.757 |
| | Pretest*DBI | 0.46 | 0.19 | 0.07 | 0.84 | **0.021** |
| 0.5 | Intercept | 13.16 | 0.74 | 11.66 | 14.65 | 0.000 |
| | Block | 0.00 | 0.22 | -0.44 | 0.44 | 0.994 |
| | Pretest | 0.50 | 0.01 | 0.24 | 0.75 | 0.000 |
| | DBI | 0.16 | 0.68 | -1.21 | 1.54 | 0.817 |
| | Pretest*DBI | 0.31 | 0.18 | -0.04 | 0.67 | **0.082** |
| 0.75 | Intercept | 14.15 | 0.60 | 12.94 | 15.36 | 0.000 |
| | Block | -0.07 | 0.23 | -0.54 | 0.39 | 0.754 |
| | Pretest | 0.66 | 0.20 | 0.24 | 1.07 | 0.002 |
| | DBI | 0.43 | 0.52 | -0.62 | 1.47 | 0.414 |
| | Pretest*DBI | -0.19 | 0.30 | -0.80 | 0.42 | 0.528 |

**Table 17. Quantile IEP Moderation Model for WRAT Part 1**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| (Intercept) | 12.74* (1.91) | 13.09* (0.56) | 13.96* (0.41) |
| Block | -0.20 (0.39) | -0.14 (0.19) | 0.00 (0.15) |
| Pretest | 0.70* (0.18) | 0.71* (0.11) | 0.50* (0.08) |
| DBI | -0.10 (1.64) | 0.57 (0.66) | 0.50 (0.43) |
| IEP | 0.90 (1.58) | 0.71 (0.58) | 0.50 (0.39) |
| DBI*IEP | 0.10 (1.76) | -0.43 (0.83) | -0.50 (0.70) |
| Quantile | 0.25 | 0.50 | 0.75 |

*$p < 0.001$

**Table 18. Quantile Race Moderation Model for WRAT Part 1**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| (Intercept) | 13.95** (0.96) | 12.17** (1.03) | 13.40** (0.60) |
| Block | -0.33 (0.34) | 0.15 (0.28) | 0.07 (0.14) |
| Pretest | 0.67** (0.11) | 0.77** (0.13) | 0.59** (0.07) |
| DBI | -1.33 (1.55) | 1.28 (1.40) | **1.33* (0.75)** |
| Race | -0.17 (0.13) | 0.31 (0.20) | **0.18* (0.09)** |
| DBI*Race | 0.50 (0.40) | -0.41 (0.38) | **-0.40* (0.21)** |
| Quantile | 0.25 | 0.50 | 0.75 |

$^{**}p < 0.001$, $^{*}p < 0.1$

**Table 19. Multilevel Quantile Impact Model for WRAT Part 2**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 5.39 | 1.58 | 2.21 | 8.57 | 0.001 |
| 0.25 | Block | -0.58 | 0.39 | -1.37 | 0.20 | 0.143 |
| 0.25 | Pretest | 1.15 | 0.20 | 0.74 | 1.55 | 0.000 |
| 0.25 | DBI | 0.24 | 0.96 | -1.68 | 2.17 | 0.799 |
| 0.5 | Intercept | 5.72 | 1.37 | 2.97 | 8.47 | 0.000 |
| 0.5 | Block | -0.19 | 0.38 | -0.95 | 0.56 | 0.609 |
| 0.5 | Pretest | 1.42 | 0.17 | 1.07 | 1.76 | 0.000 |
| 0.5 | DBI | 0.11 | 0.82 | -1.54 | 1.77 | 0.891 |
| 0.75 | Intercept | 7.11 | 1.30 | 4.49 | 9.73 | 0.000 |
| 0.75 | Block | -0.21 | 0.36 | -0.94 | 0.51 | 0.556 |
| 0.75 | Pretest | 1.29 | 0.20 | 0.88 | 1.69 | 0.000 |
| 0.75 | DBI | 0.21 | 0.86 | -1.52 | 1.95 | 0.804 |

**Table 20. Multilevel Quantile Baseline Moderation Model for WRAT Part 2**

| Quantile | Parameter | Value | Std. Error | 95% CI Lower Bound | 95% CI Upper Bound | Pr(>\|t\|) |
|---|---|---|---|---|---|---|
| 0.25 | Intercept | 5.73 | 1.56 | 2.59 | 8.88 | 0.001 |
| | Block | -0.56 | 0.44 | -1.45 | 0.32 | 0.206 |
| | Pretest | 1.44 | 0.28 | 0.86 | 2.01 | 0.000 |
| | DBI | -0.46 | 1.01 | -2.50 | 1.58 | 0.652 |
| | Pretest*DBI | -0.50 | 0.41 | -1.33 | 0.33 | 0.231 |
| 0.5 | Intercept | 6.43 | 1.54 | 3.34 | 9.52 | 0.000 |
| | Block | -0.44 | 0.49 | -1.42 | 0.54 | 0.374 |
| | Pretest | 1.60 | 0.25 | 1.10 | 2.10 | 0.000 |
| | DBI | 0.13 | 1.22 | -2.32 | 2.58 | 0.916 |
| | Pretest*DBI | -0.57 | 0.39 | -1.35 | 0.21 | 0.146 |
| 0.75 | Intercept | 7.42 | 1.55 | 4.30 | 10.55 | 0.000 |
| | Block | -0.36 | 0.50 | -1.36 | 0.64 | 0.477 |
| | Pretest | 1.61 | 0.20 | 1.21 | 2.01 | 0.000 |
| | DBI | -0.15 | 1.01 | -2.18 | 1.87 | 0.880 |
| | Pretest*DBI | -0.54 | 0.31 | -1.17 | 0.08 | **0.087** |

**Table 21. Quantile IEP Moderation Model for WRAT Part 2**

| | **Model 1** | **Model 2** | **Model 3** |
|---|---|---|---|
| (Intercept) | 5.25* (0.75) | 5.91* (1.07) | 7.68* (0.99) |
| Block | -0.33 (0.22) | -0.29 (0.33) | -0.11 (0.32) |
| Pretest | 1.00* (0.12) | 1.14* (0.18) | 1.22* (0.12) |
| DBI | 0.33 (1.12) | 1.00 (1.04) | -0.33 (0.89) |
| IEP | -1.00 (0.69) | -0.71 (1.15) | -1.00 (0.95) |
| DBI*IEP | -0.00 (1.24) | -0.86 (1.40) | -0.22 (1.62) |
| Quantile | 0.25 | 0.50 | 0.75 |

$^{*}p < 0.001$

**Table 22. Quantile Race Moderation Model for WRAT Part 2**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| (Intercept) | 7.32** (0.98) | 7.87** (1.20) | 7.89** (1.37) |
| Block | -0.73* (0.34) | -0.59· (0.34) | -0.33 (0.28) |
| Pretest | 1.18** (0.14) | 1.35** (0.16) | 1.33** (0.12) |
| DBI | -1.24 (1.21) | -1.21 (1.25) | -1.00 (1.18) |
| Race | -0.42** (0.12) | -0.51* (0.20) | -0.33 (0.40) |
| DBI*Race | 0.15 (0.43) | 0.56 (0.56) | 0.67 (0.52) |
| Quantile | 0.25 | 0.50 | 0.75 |

$^{**}p < 0.001$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

**Table 23. Year 2 Impact (March 2017) and Moderation Models for Grade 2 Mathematics Concepts and Applications**

| | Impact Model | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** |
| (Intercept) | 9.00 | 2.77 | **0.001** | 9.02 | 2.72 | **0.001** | 9.65 | 3.22 | **0.003** | 9.19 | 2.91 | **0.002** |
| Pretest | -0.08 | 0.22 | 0.731 | 0.21 | 0.34 | 0.545 | -0.03 | 0.23 | 0.882 | -0.14 | 0.23 | 0.544 |
| DBI | 2.39 | 1.85 | 0.196 | 2.38 | 1.82 | 0.191 | 0.46 | 2.92 | 0.875 | 3.15 | 2.12 | 0.137 |
| Block | -0.74 | 0.89 | 0.406 | -0.74 | 0.88 | 0.402 | -0.77 | 0.88 | 0.384 | -0.80 | 0.89 | 0.365 |
| DBI*Pretest | | | | -0.48 | 0.44 | 0.274 | | | | | | |
| IEP | | | | | | | -0.88 | 2.88 | 0.761 | | | |
| DBI*IEP | | | | | | | 3.24 | 3.72 | 0.384 | | | |
| White | | | | | | | | | | -0.11 | 3.20 | 0.973 |
| DBI*White | | | | | | | | | | -2.67 | 4.16 | 0.521 |

**Table 24. Year 3 Impact (January 2018) and Moderation Models for Grade 2 Mathematics Concepts and Applications**

| | Impact Model | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** |
| (Intercept) | 1.81 | 2.60 | 0.486 | 1.82 | 2.60 | 0.484 | 1.13 | 3.05 | 0.711 | -0.58 | 2.47 | 0.815 |
| Pretest | 0.06 | 0.21 | 0.781 | 0.14 | 0.33 | 0.676 | 0.05 | 0.22 | 0.832 | 0.09 | 0.20 | 0.641 |
| DBI | 1.85 | 1.74 | 0.289 | 1.84 | 1.74 | 0.289 | 3.25 | 2.78 | 0.242 | 4.27 | 1.81 | **0.018** |
| Block | 1.44 | 0.84 | 0.086 | 1.44 | 0.84 | 0.085 | 1.45 | 0.84 | 0.086 | 1.62 | 0.75 | **0.032** |
| DBI*Pretest | | | | -0.13 | 0.42 | 0.755 | | | | | | |
| IEP | | | | | | | 1.03 | 2.73 | 0.706 | | | |
| DBI*IEP | | | | | | | -2.30 | 3.52 | 0.514 | | | |
| White | | | | | | | | | | 8.16 | 2.72 | **0.003** |
| DBI*White | | | | | | | | | | -9.75 | 3.54 | **0.006** |

**Table 25. Year 3 Impact (May 2018) and Moderation Models for WRAT Total**

| *Predictors* | Impact Model | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* | *Estimates* | *S.E.* | *p* |
| (Intercept) | 23.90 | 2.32 | **<0.001** | 23.81 | 2.15 | **<0.001** | 23.13 | 2.27 | **<0.001** | 24.27 | 2.38 | **<0.001** |
| Block | -0.77 | 0.55 | 0.167 | -0.89 | 0.50 | 0.073 | -0.51 | 0.52 | 0.320 | -0.86 | 0.56 | 0.121 |
| Pretest | 1.15 | 0.26 | **<0.001** | 0.53 | 0.18 | 0.005 | 0.95 | 0.27 | **<0.001** | 1.10 | 0.27 | **<0.001** |
| Grade | 1.63 | 1.07 | 0.129 | 1.20 | 0.94 | 0.211 | 2.64 | 1.09 | **0.016** | 1.94 | 1.14 | 0.089 |
| DBI | -1.21 | 1.18 | 0.305 | -1.42 | 0.76 | 0.069 | -1.71 | 1.44 | 0.236 | -1.79 | 1.36 | 0.188 |
| DBI*Pretest | | | | 0.41 | 0.20 | **0.045** | | | | | | |
| DBI*IEP | | | | | | | 0.69 | 1.77 | 0.697 | | | |
| IEP | | | | | | | -2.78 | 1.35 | **0.039** | | | |
| DBI*White | | | | | | | | | | 1.67 | 2.11 | 0.428 |
| White | | | | | | | | | | -2.01 | 1.62 | 0.216 |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 6.55 | | | 5.97 | | | 5.74 | | | 6.68 | | |
| $\tau_{00}$ | 1.26 School | | | 0.81 School | | | 0.99 School | | | 1.15 School | | |
| ICC | 0.16 | | | 0.12 | | | 0.15 | | | 0.15 | | |

**Table 26. Year 3 Impact (May 2018) and Moderation Models for WRAT Part 1**

| | Impact Model | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***P*** |
| (Intercept) | 15.79 | 0.60 | **<0.001** | 15.59 | 0.49 | **<0.001** | 15.56 | 0.63 | **<0.001** | 15.95 | 0.63 | **<0.001** |
| Block | -0.06 | 0.14 | 0.658 | -0.11 | 0.11 | 0.296 | -0.06 | 0.14 | 0.691 | -0.08 | 0.15 | 0.576 |
| Pretest | 0.25 | 0.07 | **<0.001** | 0.02 | 0.08 | 0.833 | 0.21 | 0.08 | **0.005** | 0.25 | 0.07 | **<0.001** |
| Grade | -0.33 | 0.28 | 0.241 | -0.18 | 0.24 | 0.445 | -0.20 | 0.31 | 0.518 | -0.43 | 0.29 | 0.149 |
| DBI | -0.45 | 0.30 | 0.131 | -0.34 | 0.23 | 0.142 | -0.27 | 0.40 | 0.498 | -0.26 | 0.37 | 0.486 |
| DBI*Pretest | | | | 0.37 | 0.09 | **<0.001** | | | | | | |
| DBI*IEP | | | | | | | -0.38 | 0.50 | 0.446 | | | |
| IEP | | | | | | | -0.01 | 0.38 | 0.983 | | | |
| DBI*White | | | | | | | | | | -0.57 | 0.55 | 0.298 |
| White | | | | | | | | | | 0.14 | 0.43 | 0.744 |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 0.45 | | | 0.32 | | | 0.46 | | | 0.44 | | |
| $\tau_{00}$ | 0.08 School | | | 0.03 School | | | 0.06 School | | | 0.10 School | | |
| ICC | 0.15 | | | 0.09 | | | 0.11 | | | 0.18 | | |

**Table 27. Year 3 Impact (May 2018) and Moderation Models for WRAT Part 2**

| | Impact Model | | | Baseline Moderation | | | IEP Moderation | | | Race Moderation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** | ***Estimates*** | ***S.E.*** | ***p*** |
| (Intercept) | 7.61 | 1.64 | **<0.001** | 7.40 | 1.67 | **<0.001** | 6.95 | 1.62 | **<0.001** | 7.70 | 1.74 | **<0.001** |
| Block | -0.56 | 0.36 | 0.120 | -0.49 | 0.37 | 0.181 | -0.41 | 0.35 | 0.232 | -0.60 | 0.38 | 0.115 |
| Pretest | 1.14 | 0.21 | **<0.001** | 0.96 | 0.30 | **0.002** | 0.91 | 0.22 | **<0.001** | 1.10 | 0.23 | **<0.001** |
| Grade | 1.84 | 0.85 | **0.031** | 1.86 | 0.86 | **0.030** | 2.67 | 0.88 | **0.003** | 2.00 | 0.96 | **0.036** |
| DBI | -1.17 | 0.72 | 0.105 | -1.17 | 0.72 | 0.105 | -1.18 | 1.01 | 0.246 | -1.36 | 0.94 | 0.147 |
| DBI*Pretest | | | | 0.30 | 0.37 | 0.416 | | | | | | |
| DBI*IEP | | | | | | | -0.03 | 1.37 | 0.981 | | | |
| IEP | | | | | | | -1.83 | 1.10 | 0.098 | | | |
| DBI*White | | | | | | | | | | 0.57 | 1.70 | 0.739 |
| White | | | | | | | | | | -0.66 | 1.30 | 0.614 |

**Table 28. One-Sample *t*-Test Results for Mathematics Computation and Concepts and Applications in Grades 6 and 7**

| Assessment | Grade | *N* | Wave | Sample Mean | Benchmark | *t*-Statistic | *df* | *p* |
|---|---|---|---|---|---|---|---|---|
| Mathematics Computation | 6 | 26 | Fall | 8.62 | 9 | -0.32 | 25 | 0.623 |
| | | 24 | Winter | 18.79 | 14 | 1.73 | 23 | 0.048 |
| | | 24 | Spring | 18.04 | 18 | 0.02 | 23 | 0.494 |
| | 7 | 18 | Fall | 10.56 | 10 | 0.25 | 17 | 0.402 |
| | | 18 | Winter | 11.83 | 13 | -0.45 | 17 | 0.671 |
| | | 20 | Spring | 9.60 | 15 | -1.53 | 19 | 0.929 |
| Mathematics Application | 6 | 26 | Fall | 5.15 | 8 | -4.45 | 25 | >.950 |
| | | 24 | Winter | 5.50 | 11 | -7.03 | 23 | >.950 |
| | | 24 | Spring | 4.70 | 13 | -10.55 | 23 | >.950 |
| | 7 | 18 | Fall | 3.40 | 4 | -0.79 | 18 | 0.780 |
| | | 18 | Winter | 3.78 | 10 | -8.63 | 17 | >.950 |
| | | 20 | Spring | 4.85 | 10 | -6.10 | 19 | >.950 |

**Table 29. Simple Slopes Analysis for Moderation Probing**

| Project Year | Moderation | Region | Parameter | Estimate | SE | *z*-Value | *p* |
|---|---|---|---|---|---|---|---|
| 1 | Full WRAT Pt1 Baseline Moderation | -1SD | Simple Intercept | 10.79 | 0.88 | 12.28 | <.001 |
| | | | Simple Slope | -0.55 | 0.59 | -0.93 | 0.357 |
| | | Mean | Simple Intercept | 11.50 | 0.87 | 13.28 | <.001 |
| | | | Simple Slope | 0.16 | 0.48 | 0.34 | 0.74 |
| | | 1SD | Simple Intercept | 12.21 | 0.94 | 12.99 | <.001 |
| | | | Simple Slope | 0.87 | 0.61 | 1.42 | 0.161 |
| | Full WRAT Pt2 Baseline Moderation | -1SD | Simple Intercept | 3.28 | 0.88 | 3.75 | <.001 |
| | | | Simple Slope | 1.07 | 0.56 | 1.92 | 0.055 |
| | | Mean | Simple Intercept | 6.47 | 0.87 | 7.47 | <.001 |
| | | | Simple Slope | -0.08 | 0.46 | -0.18 | 0.861 |
| | | 1SD | Simple Intercept | 9.66 | 0.94 | 10.34 | <.001 |
| | | | Simple Slope | -1.23 | 0.58 | -2.12 | 0.033 |
| 3 | Full WRAT Total Baseline Moderation | -1SD | Simple Intercept | 21.75 | 1.67 | 13.02 | <.001 |
| | | | Simple Slope | -3.02 | 1.04 | -2.92 | 0.004 |
| | | Mean | Simple Intercept | 23.82 | 1.79 | 13.37 | <.001 |
| | | | Simple Slope | -1.42 | 0.76 | -1.88 | 0.06 |
| | | 1SD | Simple Intercept | 25.89 | 2.12 | 12.19 | <.001 |
| | | | Simple Slope | 0.18 | 1.14 | 0.16 | 0.872 |
| | Full WRAT Part 1 Baseline Moderation | -1SD | Simple Intercept | 15.55 | 0.46 | 33.78 | <.001 |
| | | | Simple Slope | -1.13 | 0.29 | -3.94 | <.001 |
| | | Mean | Simple Intercept | 15.59 | 0.49 | 31.82 | <.001 |
| | | | Simple Slope | -0.34 | 0.23 | -1.46 | 0.144 |

| Project Year | Moderation | Region | Parameter | Estimate | SE | *z*-Value | *p* |
|---|---|---|---|---|---|---|---|
| | | 1SD | Simple Intercept | 15.63 | 0.57 | 27.50 | <.001 |
| | | | Simple Slope | 0.45 | 0.33 | 1.37 | 0.169 |
| 3 | G2 Mathematics Concepts and Application | Non-White | Simple Intercept | -0.58 | 2.47 | -0.24 | 0.815 |
| | | | Simple Slope | 4.27 | 1.81 | 2.37 | 0.018 |
| | | White | Simple Intercept | 7.58 | 2.99 | 2.59 | 0.011 |
| | | | Simple Slope | -5.48 | 3.05 | -1.80 | 0.072 |

# Appendix A

Project Logic Model (Program: DEV96: Intensive Intervention in Mathematics)[10]

## Inputs

Existing RTI/MTSS structures in place in schools

**Resources:**

- Release time for intervention teams to meet and attend training and coaching sessions
- Support staff time for coordination
- Training materials
- Trainers
- Coaches

## Key Program Components/Activities

**Readiness & buy-in:**

- Ensure support from district and school leaders and buy-in from relevant staff.
- Provide information about project goals and progress updates.

**Professional development training** to develop knowledge and skills to implement DBI in mathematics, including:

- New pedagogical strategies
- New strategies for using data to individualize intervention
- Use of ongoing progress monitoring and diagnostic assessment data

**Formative evaluation:**

- Complete an initial needs assessment.
- Determine schools' progress with DBI implementation.
- Identify strengths and challenges to inform future planning.

**Implementation coaching:**

- Engage in planning, review of data, evaluation of progress, and student-level planning.
- Support identification and implementation of school or district policies and procedures, as needed.
- Develop strategies for engaging families and involving them in intervention planning and progress reviews.

## Outcomes

### Proximal Outcomes/Mediators

**School/District:**

- Improved systems for serving students with intensive mathematics learning needs
- Increased appropriate identification and placement of students across tiers of RTI

**Intervention teams:**

- Data use to individualize and evaluate mathematics instruction/intervention
- Higher staff confidence in ability to address intensive mathematics learning needs

**Families:**
Enhanced participation in education planning, programming for children with disabilities and with intensive mathematics learning needs

### Distal Outcome

**Student achievement:**

- Improved mathematics achievement for students with disabilities who have intensive mathematics learning needs
- Improved mathematics achievement for other students with intensive mathematics learning needs who do not have identified disabilities

**Families:**
Increased satisfaction with educational programming for students with disabilities

[10] Note: This logic model came from our approved NEi3 evaluation plan.

# Appendix B

## Other Project Evaluation Activities

Throughout the implementation of this project, we engaged in three formative evaluation activities that were outside the scope of our planned impact evaluation but that provided additional useful context for our work. We describe these activities in the sections that follow.

## Monitoring DBI and MTSS Implementation Progress

As noted in the description of project activities, project staff conducted intake interviews to determine baseline performance of components of DBI and MTSS in mathematics. In addition, they conducted annual implementation pulse check interviews in the spring of each implementation year to formatively evaluate implementation fidelity progress of systemic features of DBI and MTSS in mathematics.

Pulse checks took place prior to implementation to determine baseline performance and annually in the spring of each implementation year through interviews with school implementation teams. A member of the project staff and each site's project coach led the interviews using a set of questions derived from implementation fidelity rubrics and interviews, which were initially developed by the National Center on Intensive Intervention and the Center on Response to Intervention.[11] Interview participants included members of each school site's intervention team (e.g., principals, school psychologists, intervention specialists, special educators), who had participated in ongoing professional development and coaching throughout the year. Following the interviews, interviewers independently rated sites' implementation against rubric indicators. Scores ranged from 1–5, with "1" indicating little or no implementation and "5" indicating strong or full implementation. After scoring independently, interviewers compared their scores, discussed, and rectified any discrepancies. The average implementation score for components of DBI and MTSS, respectively (e.g., assessment, data-based decision making), were then calculated. Those subscores were then used to compute an overall average implementation score. On average, schools scored 2.4 at baseline for indicators of DBI in mathematics (range of 1.2–3.6) and improved to an average score of 3.7 (range of 3.0–4.5) by the end of the project. For indicators of MTSS in mathematics, schools started with an average baseline score of 2.8 (range of 1.8–3.9) and improved to an average score of 3.7 (range of 3.0–4.5).[12]

Trends showed that as schools achieved growth on indicators of DBI (e.g., intensification practices, decision rules, using individualized student data to inform decisions), they also tended to show growth on indicators related to general MTSS processes such as having school-wide screening and progress monitoring assessments and procedures in place, holding regular data meetings, and providing time for Tier 2 intervention to occur. We observed this trend across nearly all elementary and middle school sites, providing evidence to suggest that implementation

[11] Modified to reflect MTSS terminology.
[12] The district had been implementing tiered supports in reading for several years prior to project commencement, although district leaders noted challenges with Tier 3 (i.e., intensive intervention), which was part of the impetus for their interest. Given this, we were not surprised by their higher initial overall MTSS implementation scores.

of MTSS may not need to be linear (i.e., that Tier 1 must be in place before Tier 2, and so forth). This observation contrasts with conventional wisdom about MTSS, which typically suggests that implementation must start at Tier 1. This approach may be problematic because it can delay implementation of more intensive tiers of support for students who need them. We believe a comparison of approaches to implementation warrants further study.

## Study of Alignment Between Mathematics Instruction and Intervention Materials

Lack of alignment between instruction and intervention programs is a common barrier to implementation of interventions for struggling students. Throughout the course of this project, several school and district staff noted this concern in reference to their core mathematics program and their typical intervention programs. To better understand and document these points of alignment and misalignment, project staff conducted an analysis of these programs across grades 1-5, with a specific focus on their use of mathematics instructional practices and mathematics vocabulary. Findings from this review revealed that teachers' perceptions about misalignment were accurate. We observed little overlap between programs both in terms of their use of mathematics practices, and mathematically precise vocabulary, where overlap between programs ranged from just 6.3% to 24%. A full discussion of this analysis, including instructional recommendations for addressing points of misalignment, was reported in Nelson et al., (2020).

## Gathering Feedback About DBI Implementation Through Interviews With Families

To better understand parents' perceptions regarding DBI implementation and their experiences collaborating with their children's schools, we conducted a series of phone interviews with parents of students receiving intensive intervention in mathematics in participating schools. School principals and other staff involved in DBI implementation recommended parents for the interviews and provided parents' contact information. We invited these parents to participate in telephone interviews regarding their perceptions and experiences communicating and collaborating with their children's schools. We provided parents a one-page description of the interview and asked them to return a signed consent form to indicate their willingness to participate. Nineteen parents returned signed consent forms, and we were successful in conducting interviews with 15 of these parents. Interviewees had children in eight schools in the district; of these schools, seven were elementary schools and one was a middle school. Five of these parents had children who were identified as having a disability, 12 were parents of elementary school students, and three were parents of middle school students. We asked parents for their perceptions regarding what worked well when communicating with their children's schools and what they perceived as barriers to successful parent-school communication and collaboration. Interviews lasted approximately 20 minutes.

Overall, parents reported satisfaction with the amount of communication they received from their children's schools. Practices that worked well for parents included frequent written communication with teachers, meeting with the intervention team during fall conferences to discuss intervention planning, sharing academic data and discussing the data at conferences, and demonstrating commitment to learning about students' needs and individualizing instruction. Across interview participants, there was significant variation in the amount of communication that parents reported receiving. For example, one parent reported receiving weekly written progress updates while another reported that progress updates were received only with report cards.

Several parents discussed the positive impact that they perceived from the intensive intervention in mathematics that their children had received. For example, parents reported that their children showed more confidence in mathematics, were able to complete homework independently, were happier about going to school, and understood more mathematics concepts due to the individualized instruction they received. Several parents spoke about how their children needed more extensive explanation of mathematics concepts than was available during core instruction and were pleased that intensive intervention provided this opportunity. Parents also were appreciative of how interventionists took the time to get to know their children's needs and to tailor instruction to meet those needs.

The interviews also revealed several barriers and challenges to successful communication and collaboration with school staff. A few parents noted a lack of communication with intervention teachers or special education teachers. For example, one parent commented that he/she had never met the interventionist and had little idea about what work was being done during the mathematics intervention. In addition, some parents reported that communication from the general education teacher was not always relevant to their children who were participating in intervention outside of the general education classroom. Another barrier reported by a few parents was a perception that some school staff lacked the skill or patience to work with their children with intensive needs, especially relative to behavior issues. Other reported challenges included confusion about progress monitoring for students performing below grade level and frustration regarding the special education eligibility process. We provide a more detailed discussion of our findings and related recommendations in Weingarten, Zumeta Edmonds, and Arden (2020).