Inclusive and Equitable Impact:

Exact Path Meets the Needs of Diverse Learners

Edmentum Efficacy Research & Learning Engineering
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Abstract

Edmentum offers a personalized learning platform called Exact Path. Over the past five years, about 56 schools and districts in Virginia have implemented the program. This quasi-experimental study, designed to meet ESSA Tier 2 evidence and What Works Clearinghouse standards with reservations, aimed to investigate the efficacy of Exact Path in Norfolk Public Schools. The study estimated the effects of the program for diverse groups of students in order to inform our understanding of the district context and guide instructional decisions. The study found that Exact Path was positively related to Math achievement for students in Grades 3 through 8. The findings suggest that Exact Path could be an effective tool for improving student success in Virginia and similar contexts. These results have implications for educators, policymakers, and researchers interested in improving academic outcomes through personalized learning.

Context

The Norfolk Public Schools district operates 51 schools in total, out of which 32 have been designated as Title I schools (Norfolk Public Schools, 2023). Notably, the area has a high poverty rate, recently reported at 14.7% in its entirety (City Data, 2021). Often, systemic inequities faced by under resourced districts can lead to reduced access to quality education (Eiraldi et al., 2015; Reardon, 2011; Sirin, 2005). The recent COVID-19 pandemic has amplified these longstanding educational disparities (Gee et al., 2023), with technology becoming an increasingly integral part of the education landscape (OECD, 2020; United Nations, 2020).

Personalized learning tailors instruction to students' learning needs and abilities (Tomlinson, 2014; U.S. Department of Education, 2017). It has been proposed as a solution in contexts where access to quality education is uneven (Pane et al., 2015). The approach may help address disparities in educational access by providing all students with equitable opportunity to succeed academically, regardless of their background (Pane et al., 2015; Murphy et al., 2016, Pane et al., 2017). Technology platforms can provide educators with real-time data on student progress (Nedungadi & Raman, 2012), enabling them to make informed instructional decisions and offer targeted support (Means et al., 2013; U.S. Department of Education, 2017). However, there is

much to learn following the recent pandemic about the efficacy of technology education (Hodges et. al, 2020; Goldhaber et al., 2022). More research is needed to evaluate the efficacy of technology-enhanced learning in various contexts, especially for students with diverse backgrounds and needs (Means et al., 2013; Shenmshack & Spector, 2020).
While personalized learning is a general term, for this project we define it as being composed of three interrelated concepts (Basham et. al, 2016). First, a personalized trajectory of learning in a virtual school setting should be grounded in the learning progression of specific disciplinary knowledge, such as Math or Reading (National Research Council, 2001; Wilson, 2023). The underlying content of what a student should learn, and how that content advances over time, should be the same online as in a traditional curriculum, because the learning progression provides a roadmap for instruction and must be aligned with state standards (Pearson et. al, 2014; Wilson, 2023). Second, personalized learning accommodates, and provides access to, individual learning paths where students progress through a program of instruction that meets their needs, whether these needs are remedial, grade-level instruction, or enrichment (Means et al., 2014; Pane et al., 2015). An online program may provide instructional flexibility. Third, for a learning path to be truly individualized, the person needs to be fairly, accurately assessed at the onset of their learning so that their location on the underlying learning progression is captured accurately. This assessment provides guidance for instruction; personalized learning platforms typically include an algorithm to recommend where each student should begin their journey in learning progression, so that the instruction students receive is optimally suited to their current achievement level.

Combining advances in educational technology with learning engineering and psychometrics, the Exact Path program offers instruction in Math, Reading, and Language Arts. It is grade agnostic, meaning that the learning path offered to students depends on their performance on an initial assessment. Learning paths accommodate students still struggling with grade-level precursor skills and those best served by above-grade-level enrichment opportunities. Following initial assessment and placement into a learning path, a student moves through their learning trajectory and is assessed at key touchpoints via progress checks. After each progress check, the student moves on or the learning path is remediated, and the student referred to a precursor building block if necessary.

As researchers embedded in the organization, we wished to better understand how Exact Path usage relates to student outcomes. The following research questions guided the design and analyses used in this study.

- To what extent, if any, does the use of Exact Path affect Norfolk student achievement outcomes as measured by Renaissance Star scores during the academic year 2021-2022?
- Do the intervention effects differ for students according to their demographic characteristics and backgrounds?

Methods

Research Design

To investigate whether Exact Path was related to higher academic achievement, the study used a nonrandomized comparison group, pretest-posttest quasi-experimental design. The design meets What Works Clearinghouse (WWC) 5.0 standards with reservations (U. S. Department of Education, Institute of Education Sciences, & What Works Clearinghouse, 2022). According to the WWC, a quasi-experimental design (QED) uses a non-random process to form the intervention and comparison conditions. The WWC allows groups to be formed using a variety of methods as long as the groups are mutually exclusive. That is, units (e.g., students or schools) can only be analyzed as a member of a particular group. Further, in a quasi-experimental study, the WWC accepts assignment to the intervention based on observed characteristics. In this study, assignment to experimental conditions was carried out at the individual student level. To create the intervention and comparison groups, the usage indicator for the intervention (Exact Path) was created by examining the number of skills completed. Propensity score matching was employed to establish intervention and comparison groups, ensuring comparability between the two. The "nearest neighbor" method was used for matching, which matches each intervention unit with the comparison unit that has the closest propensity score (Stuart, 2010). This approach facilitated the creation of matched intervention and comparison groups. Baseline equivalence was determined by prior test scores, gender, ethnicity, demographic groups, Individualized Education Program (IEP) and English learner (EL) status (What Works Clearinghouse, 2022). After the appropriate group assignments were made, the intervention effects were determined by estimating the differences in outcomes between the intervention and comparison groups.

Outcome Measures

The Renaissance Star Math Enterprise assessments (Star), developed by Renaissance Learning, Inc., are a series of computer-adaptive assessments designed to measure student progress, achievement, and growth in key academic areas (Renaissance Learning, 2022). The outcome measures for the study were the Spring 2022 Star tests in Math. The reliability coefficients for grade 3-8 Math Star tests ranged from 0.91 to 0.93 (Renaissance Learning, 2022), indicating that the assessments provided consistent results when measuring student knowledge and skills in grade 3-8 Math. Renaissance Star meets WWC criteria as an independent measure for this study, because Renaissance Star is not developed by the intervention developer and it is listed as a known independent measure required for findings to be designated as main in mathematics domain in WWC Study Review Protocol 5.0 (What Works Clearinghouse, Institute of Education Sciences, U. S. Department of Education, 2022). Prior achievement (Fall 2021 Star test), gender, ethnicity, demographic characteristics, special education status and English learner status were used as control variables for the outcome measures in this study.

Data

Student level data was collected from Norfolk Public Schools in Virginia. Our sample consisted of students from 34 elementary schools and 13 middle schools within the district that were Exact Path partners during the 2021-2022 academic year. The data contained students' test scores and demographic information in Grades 3-8 for the academic year 2021–2022. We analyzed the data in combination with Exact Path Learning Path data in our system. Our analytic sample consisted of all the students for whom the Exact Path curriculum was made available by instructor choice, and students who had valid Star test scores in the Star testing windows from Fall 2021 to Spring 2022. All students in the sample were assigned a learning path via the Star diagnostic tests. Classroom implementation was determined by the teacher or school administration. Since Exact Path was assigned to students from grade 3 to grade 8 to learn Math in the district, our study focused on students from those grades and that subject.

Analytic Sample

The sample was comprised of 8,704 students from 34 elementary schools and 13 middle schools. Of the elementary students in the sample, 80.5% came from Title I schools, while 50.9% of the middle school students were from Title I schools. The average school-level free/ reduced lunch price percentage is 79.9% in elementary schools, and 73.6% in middle schools. A majority (60.0%) of the students were Black students; about 49.0% were Female, and around 12.0% reported Hispanic as their ethnicity. See Table 1.

Table 1

Demographic Characteristics of the Sample for Elementary and Middle School (N = 8,704)

Baseline characteristic	Grade 3-5 *(n = 5,090)*		Grade 6-8 *(n = 3,614)*	
	n	*%*	*n*	*%*
Female	2500	49.1	1766	48.9
Hispanic (Ethnicity)	619	12.2	434	12.0
Asian	94	1.8	81	2.2
Black	3025	59.4	2222	61.5
Native American	59	1.2	44	1.2
Pacific Islander	22	.4	23	.6
Two or More Races	378	7.4	277	7.7
White	1512	29.7	967	26.8
IEP	758	14.9	586	16.2
EL	283	5.6	244	6.8

Note. Data are reported as number and percentage. Percentages are not exact because of rounding. Student socioeconomic status was not available. IEP = Individualized Education Program, EL = English learner.

After reviewing the demographic characteristics of the sample and noting the different sample sizes in middle school versus elementary school, we investigated personalized learning path progressions for the sample of students (Appendix A). Table A1 in Appendix A shows that middle school students completed much fewer skills than did elementary school students on average.

The intervention seemed to be implemented differently in middle versus elementary school. Alternatively, the skills themselves may be more difficult since presumably middle school Math skills are harder. Either way, the students' participation in Exact Path seemed sufficiently different that it warranted disaggregating the sample. Following these analyses, we developed a plan for creating intervention and comparison groups.

Intervention/Comparison Groups

We defined the intervention group as students who had both Fall 2021 and Spring 2022 Star assessment scores and completed at least eight Exact Path skills in math. That is, students needed to complete at least eight skills within the seven sub-domains of math (Algebra & Expressions; Counting & Cardinality; Fractions & Ratios; Functions; Geometry; Measurement, Data, & Statistics; and Numbers & Operations). At least eight skills were chosen as the definition for Exact Path based on prior research (Randel, 2018a; 2018b) and substantive understanding of the Exact Path curriculum. For example, Exact Path assigns skills in groups of three to four. Using eight skills helps ensure that students are working their way through the learning progression and are using Exact Path as intended. Students are expected to complete a set of skills, take a progress check, and move further along the learning progression. Also, up to 31 skills are available for math. This means 12 skills represent approximately one semester's worth of learning on the learning progression. Since the study examined student achievement from spring 2021 to spring 2022, at least eight skills were deemed a reasonable definition of Exact Path use. The number of skills completed by students in the Exact Path intervention group varied (see Appendix A for details).

We defined the control group as students who had both Fall 2021 and Spring 2022 Star assessment scores and didn't use Exact Path (0 skill). This definition helped ensure that students in the control group were not using Exact Path. This definition of the control group also ensured that no students were included in both groups. In other words, the study groups were mutually exclusive and were in accordance with the group design guidelines set by the What Works Clearinghouse (What Works Clearinghouse, 2022).

Baseline Equivalence

Demonstrating the similarity of the groups before the start of an intervention is a critical part of quasi-experimental studies (What Works Clearinghouse, 2022). Baseline equivalence between the intervention and comparison students was established using propensity score matching, a method that involves pairing each intervention student with a control individual who has the closest propensity score. This process, referred to as "nearest neighbor" matching, was conducted without any missing baseline or outcome data, ensuring a robust comparison (Stuart, 2010). Baseline equivalence was estimated for each cohort. According to What Works Clearinghouse's criteria, a study can meet baseline equivalence if: (a) the baseline difference between intervention and comparison groups is less than 0.05 standard deviations or (b) the baseline difference is less than or equal to 0.25 standard deviations and the baseline measure(s) are included as covariates(s) in the analysis model (What Works Clearinghouse, 2022).

As illustrated in Table 2 and Table 3, baseline equivalence for intervention and comparison students was established on the basis of prior test scores (Fall 2021 Star test), gender, ethnicity, demographic groups, special education status and English learner status. The results indicated that baseline characteristics were similar between the intervention and comparison groups, with baseline differences of less than 0.25 standard deviations for both Grade 3-5 and Grade 6-8. Means and standard deviation are reported for each baseline measure for both the intervention and the comparison groups. There are no Pacific Islander students in the matched sample for middle school students. The baseline characteristics differences between intervention and comparison student groups were all less than 0.25 standard deviations, in line with the What Works Clearinghouse (WWC) guidelines (2022). Baseline measures that are more than 0.05 and less than 0.25 will all be included as covariates in the analysis model.

Table 2

Pre-Intervention Sample Sizes and Characteristics after Matching (Grade 3-5, N= 1584)

Baseline characteristics	Intervention		Comparison			
	M	*SD*	*M*	*SD*	ES	*p*-value
Percent Female	44.7%	.50	48.1%	.50	.07	.22
Percent Hispanic (Ethnicity)	12.7%	.33	12.0%	.32	.02	.68
Percent Asian	2.8%	.16	1.7%	.13	.08	.17
Percent Black	62.4%	.62	58.9%	.59	.06	.20
Percent Native American	1.3%	.11	1.5%	.12	.02	.80
Percent Pacific Islander	0.2%	.05	0.5%	.07	.04	.32
Percent Two or More Races	5.1%	.24	7.2%	.26	.08	.10
Percent White	29.0%	.45	31.1%	.46	.05	.45
Percent IEP	19.3%	.40	19.4%	.40	.00	.94
Percent EL	7.3%	.26	5.8%	.23	.07	.28
Prior test score	529.94	113.34	529.13	118.04	.01	.91

Note. *M* = Mean, *SD* = Standard Deviation, IEP = Individualized Education Program, EL = English learner, Prior test score = Fall 2021 Star test score. ES = Effect Size.

Table 3

Pre-Intervention Sample Sizes and Characteristics after Matching (Grade 6-8, N=626)

Baseline characteristics	Intervention		Comparison			
	M	*SD*	*M*	*SD*	ES	*p*-value
Percent Female	51.6%	.50	49.5%	.50	.04	.75
Percent Hispanic (Ethnicity)	14.5%	.34	12.4%	.32	.07	.66
Percent Asian	0.0%	.00	0.2%	.14	.01	.00
Percent Black	59.7%	.48	62.9%	.49	.07	.62
Percent Native American	3.2%	.18	1.1%	.10	.21	.35

Percent Two or More Races	3.2%	.18	6.7%	.25	.14	.16
Percent White	27.5%	.45	28.1%	.45	.01	.86
Percent IEP	21.0%	.41	24.3%	.43	.08	.55
Percent EL	8.1%	.27	7.8%	.27	.01	.94
Prior test score	629.93	101.83	624.36	114.43	.05	.52

Note. *M* = Mean, *SD* = Standard Deviation, IEP = Individualized Education Program, EL = English learner, Prior test score = Fall 2021 Star test score. ES= Effect Size.

Analysis Model

A two-level Hierarchical Linear Model (HLM) (Raudenbush & Bryk, 2002) was fitted to the data to estimate program impacts on student outcomes. HLM takes into account the nested structure of the data—students nested within schools—to estimate intervention effects and can incorporate relevant variables from the different levels to examine potential moderators in light of study questions (Raudenbush & Bryk, 2002). Impacts of Exact Path were estimated by comparing outcomes for students who were assigned to the intervention and comparison groups. The impact analyses focused on the effect of Exact Path on students' Star test outcomes. To improve the precision of the estimates, prior achievement, gender, ethnicity, demographic groups, special education status and English learner status were included in the model as student-level covariates; school Title I status and school-wide rates of free-reduced lunch were included in the model as school-level covariates. School level information was obtained from the National Center for Education Statistics (NCES) website (National Center for Education Statistics, 2023). Mixed effects models were estimated utilizing the "lme4" package in the R statistical programming environment (Bates et. al, 2015; Gelman & Hill, 2006). Missing data was handled using listwise deletion (Schafer & Graham, 2002; What Works Clearinghouse, 2022). The baseline measures and outcomes were critical to evaluate the effectiveness of the intervention. Given our large sample size, students with missing data on these performance measures were eliminated from the sample (What Works Clearinghouse, 2022).

Considering unequal allocations to intervention and comparison for different grades, each grade was marked with block dummies. Dummy variables representing blocks were included in the model, producing fixed intercepts for blocks (the mean outcome may differ for each block, apart from the effect of the intervention). Because outcomes may differ by grades, controlling for grade dummy variables, just like controlling for any other covariates likely to be related to the outcome, can reduce the standard error of the impact estimate.

The following two-level HLM was applied to estimate the various intervention impacts (model formula [1]):

$$\boldsymbol{Outcome}_{\mathbf{ijk}} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}_1(\boldsymbol{Baseline})_{\mathbf{ijk}} + \boldsymbol{\beta}_2(\boldsymbol{Intervention})_{ijk} + \boldsymbol{\beta}_{\mathrm{I}}\Sigma(\boldsymbol{I})_{\mathbf{ijk}} + \boldsymbol{\beta}_{\mathrm{T}}\Sigma(\boldsymbol{T})_{\mathbf{jk}} + \Sigma \boldsymbol{v}_{\mathrm{b}}\boldsymbol{Block}_{\mathbf{k}} + \mu_{\mathbf{ijk}} + \boldsymbol{e}_{\mathbf{ijk}}$$

Where subscripts *i*, *j* and *k* denote student, school and block, respectively. *Outcome* represents student Star achievement in Spring 2022; *Baseline* represents the baseline measure of the outcome (Star achievement in Fall 2021); *Intervention* is a dichotomous variable indicating student assigned to the intervention condition; and ***I*** and ***T*** are two vectors of control variables for students and schools, respectively, measured prior to exposure to the intervention. In this case, student level control variables include pretest (Fall 2021), demographics, ethnicity, gender, IEP status, and English Learner status; school level control variables include school average Free-reduced Lunch percentages and school Title I status. Also, *v* represents a vector of fixed effects for k-1 block. Lastly, μ represents a random variable for school level (clustering groups), and $\boldsymbol{e_{ijk}}$ is an error term for individual sample members. In this model, the intervention effect is represented by $\boldsymbol{\beta_2}$, which captures covariate-adjusted intervention/comparison differences in the outcome variable. $\boldsymbol{\mu_{jk}}$ captures random effects (intercepts) of schools, which accounts for the positive intra-class correlations in the data.

Moderation analysis was conducted to provide information on whether Exact Path has differential effects for certain groups of students (Raudenbush & Bryk, 2002). We tested reasonably sized student groups defined by characteristics (such as gender, ethnicity) to determine if and how effects vary according to demographic characteristics. To conduct moderation analyses, HLM regressions were modified by adding the moderators' covariates and as grand-mean centered interactions with the treatment indicators. Simple extensions to model [1] allowed us to examine differential effectiveness across subgroups by including interactions between treatment status and one of the variables in ***I*** and ***T***. Model [2], for example, shows how we can estimate separate program effects for subgroups of students:

$$\boldsymbol{Outcome}_{\mathbf{ijk}} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}_1(\boldsymbol{Baseline})_{\mathbf{ijk}} + \boldsymbol{\beta}_{2\mathrm{F}}(\boldsymbol{Intervention})_{ijk}(\boldsymbol{Female})_{ijk} + \boldsymbol{\beta}_{2\mathrm{M}}(\boldsymbol{Intervention})_{ijk}(\boldsymbol{Male})_{ijk} + \boldsymbol{\beta}_{\mathrm{I}}\Sigma(\boldsymbol{I})_{\mathbf{ijk}} + \boldsymbol{\beta}_{\mathrm{T}}\Sigma(\boldsymbol{T})_{\mathbf{jk}} + \Sigma\boldsymbol{v}_{\mathbf{b}}\boldsymbol{Block}_{\mathbf{k}} + \mu_{\mathbf{jk}} + \boldsymbol{e}_{\mathbf{ijk}}$$

The only difference between this model and [1] is that the term $\beta_2(Intervention)_{ijk}$ is replaced by two terms that interact the intervention group variable $Intervention_{ijk}$ with dichotomous variables (for example, female and male). Program impacts on female and male learners are captured by the coefficients β_{2F} and β_{2M}, respectively. To examine student demographic analyses, we statistically tested the hypothesis $\beta_{2F} = \beta_{2M}$, so that we can establish whether program impacts were statistically different.

Results

The research questions for this study focused on the extent to which Exact Path was associated with student success in Star Math tests. A series of hierarchical linear models was fitted for elementary school data and middle school data separately. For each sample, the unconditional model was estimated without any student-level or school-level predictor variables. Then student-level variables were added to the model one by one to test their significance. Relevant level-one variables were retained, and school-level predictors were examined. Coefficients along with fit statistics for the hierarchical linear regression models are reported in Appendix B.

Exact Path Positively Impacted Elementary Students' Math Achievement

The results in the following tables are predicted values from the HLM models that adjust for the differences in characteristics between intervention and control groups, as described in the analysis section. Table 4 outlines the findings from the post-model marginal means estimation, displaying positive effects of the intervention for the elementary school full sample. Students in grades 3 to 5, who used Exact Path to complete at least 8 skills, demonstrated significantly higher math achievement as compared to their peers in the comparison group ($p<.001$).

Results from demographic analyses (where groups were of considerable size in elementary schools) are also reported in Table 4. On average, Black students in the intervention group exhibited statistically significant higher Math performance compared to Black students in the control group ($p < 0.001$). On average, female students had lower test scores as compared to males, but female students in the intervention group showed statistically significant improvement in Math scores relative to the female students in the control group ($p < 0.001$), registering an effect size of 0.16. English learners who utilized Exact Path as part of the intervention group showed statistically significant improvement in Math performance over their counterparts in the comparison group, with an effect size of 0.26. Due to the small sample sizes for Asian, Native American, and Pacific Islander students, we have opted not to report these findings to prevent potential misinterpretation.

In terms of practical significance, the effect size of 0.26 translates into an improvement index of +10, showing the expected change in percentile rank if a comparison student had received the intervention. An English learner at the 50th percentile at pretest, for example, could be expected to shift into the 60th percentile had she received the intervention as compared to her peers. The respective improvement indexes for students with IEPs, female students, Black students, and students identified as Two or More Races were: +3, +6, +7, and +18.

Table 4
Intervention Outcomes and Estimated Effects (Grade 3-5, N=1584)

Baseline characteristics	Intervention		Comparison		Intervention vs. Comparison			
	M	*SD*	*M*	*SD*	Total N	Effect Size	*p*-value	Improvement Index
Full Sample	619.79	229.96	603.38	146.96	1584	.11	<.001	+4
Female	615.44	168.36	597.15	113.07	746	.16	<.001	+6

Hispanic	604.46	78.55	591.94	70.49	192	.18	.27	+7
Black	604.49	154.52	586.60	102.35	949	.17	<.001	+7
Two or More Races	627.29	77.85	593.24	70.68	105	.48	.02	+18
White	615.77	103.80	605.77	82.94	468	.12	.16	+6
IEP	596.32	86.87	590.55	74.76	308	.08	.51	+3
EL	621.32	80.39	602.19	72.83	99	.26	.02	+10

Note. *M* = Mean, SD = Standard Deviation, IEP = Individualized Education Program, EL = English learner, p-value reported in two decimal places. II = Improvement Index.

Exact Path Positively Impacted Middle School Students' Math Achievement

Table 5 presents the results of the post-model marginal means estimation, showing positive intervention effects for the middle school full sample. Students in grades 6 to 8 who used at least eight skills of Exact Path exhibited statistically significantly higher Star scores compared to their peers in the comparison group (p = 0.01). Results from demographic group analyses (where groups in middle school were of considerable size) are also presented in Table 5. Our sample size for Hispanic (ethnicity), English Learners, Asian, Native American, and Two or More Races in Middle school were small, therefore, we have not reported those effects to prevent any potential misinterpretation. Among female students, those in the intervention group who used Exact Path demonstrated significantly better Math performance than their counterparts in the comparison group. This was evidenced by an effect size of 0.21. An effect size of 0.21 translates into an improvement index of +8, which corresponds to performance shift for the average student from the 50th to the 58th percentile, suggesting that a female student who used Exact Path could expect to gain 8 percentile points as compared to a female student in the comparison group, i.e., moving from a 50th to 58th percentile rank. Additionally, statistically significant positive intervention effects were observed among Black students, represented by an improvement index of +5. Effects were not significant at the .05 level for White students or Students with IEPs.

Table 5

Intervention Outcomes and Estimated Effects (Grade 6-8, N=626)

Baseline characteristics	Intervention		Comparison		Intervention vs. Comparison			
	M	*SD*	*M*	*SD*	Total N	Effect Size	*p*-value	Improvement Index
Full Sample	660.06	181.21	641.14	177.52	626	0.11	0.01	+4
Female	668.81	140.71	638.82	139.88	311	0.21	<.001	+8
Black	637.47	142.99	619.61	140.34	392	0.13	0.05	+5
White	671.12	103.49	654.80	100.41	174	0.16	0.22	+6
IEP	641.98	113.87	623.60	115.29	150	0.16	0.18	+6

Note. *M* = Mean, *SD* = Standard Deviation, IEP = Individualized Education Program, *p*-value reported in two decimal places.

Conclusion

Our research investigated the effectiveness of Exact Path on students' Math achievement, as measured by Renaissance Star assessment in the 2021-2022 academic year. The quasi-experimental design demonstrated that students who used Exact Path improved in their Star Math scores more than a comparison group with similar characteristics. Exact path positively impacted students' Math achievement in both elementary and middle schools. Examining students across various demographic and characteristic groups, we found that female students, Black students, English learners, or those identifying as Two or More Races in elementary schools exhibited statistically significant higher Math achievement in the intervention group compared to their counterparts in the comparison group. Similarly, middle school students from these groups also experienced positive intervention effects. However, these effects did not reach statistical significance in middle school, except female students and White students. We note the limited sample size of English Learners in middle school.

By following the guidelines of the What Works Clearinghouse (WWC), the study ensures the validity of its findings and provides evidence-based recommendations for improving student achievement. The research concludes that Exact Path works well for diverse populations of students in Grade 3 through Grade 8. It highlights the potential of Exact Path as a valuable tool in supporting students' learning, academic growth, and success. The measure is used to establish baseline equivalence; the baseline and outcome measures are independent of Exact Path and thus are not over-aligned to the intervention. The study had no confounds.

The study meets criteria set forth by Every Student Succeeds Act (U.S. Department of Education, 2016). The Department of Education considers a quasi-experimental study to be "well-designed and well-implemented" if it receives a Meets WWC Design Standards with Reservations rating or is of equal quality (U.S. Department of Education, 2016). The study also meets the ESSA criteria for statistically significant positive effects. These two aspects of the study indicate that it qualifies as providing Moderate Evidence (Level 2) on the effectiveness of Exact Path.

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Appendix A. Exact Path Skills Completed

Table A1

Skills Completed Varied Across Grades in the Intervention Group

Math	Total # of Skills Completed	Average # of Skills Completed
Grade 3	5508	13.08
Grade 4	6567	13.27
Grade 5	7407	11.09
Grade 6	2190	6.87
Grade 7	883	4.65
Grade 8	819	7.00
Full Sample	23374	10.58

Table A2

Number of Students in the Intervention Group Completing Math Skills (N=2210)

Skills Completed	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade8	Full Intervention
8 skills	40	35	62	43	15	9	204
9 skills	19	45	68	19	11	20	182
10 skills	22	39	45	21	9	7	143
11 skills	13	27	36	16	11	6	109
12 skills	20	27	45	12	6	7	117
13 skills	19	25	31	10	4	3	92
14 skills	20	15	21	6	3	5	70
15 skills	14	23	27	5	1	2	72
16+ skills	142	151	157	42	11	9	512
Total	421	495	668	319	190	117	2210

Appendix B. Coefficients and Fit Statistics of the Hierarchical Linear Regression Model

We included those variables that demonstrated significant effects in the final model, and we reported their perspective coefficients. Table A1 presents the results of the final model using the sample of elementary school students. School level predictors average Free-reduced Lunch percentages (p=0.73) and school Title I status (p = 0.40) were not statistically significant predictors. Intervention emerged as a statistically significant positive predictor (p < 0.001), indicating that completing at least 8 skills in Exact Path was associated with significantly improved Math performance. Gender, Hispanic (ethnicity) and IEP status were statistically significant suggesting that female students, Hispanic (ethnicity) students, and students with IEPs tend to have lower Math achievement compared to their counterparts. English learner status did not prove to be statistically significant predictors. Black students on average received lower test scores compared to their peers ($p < 0.001$). Although neither English learner status nor some racial groups were not statistically significant predictors, they were included in the final model due to the baseline differences of racial groups falling between 0.05 and 0.25 (What Works Clearinghouse, 2022).

Table B1

Two-level Hierarchical Linear Regression Model for Elementary Students (N=1584)

Variable	Coefficient	SE
Intercept	203.71***	11.04
Intervention	16.41***	4.09
Fall	0.79***	0.02
Gender	-7.22***	2.11
IEP	-25.16***	3.07
EL	1.98	8.06
Hispanic (Ethnicity)	-11.91*	6.13
Native American	4.36	14.23
Pacific Islander	3.50	24.67
Two or More Races	4.96	7.04
Asian	13.01	11.88
Black	-13.42***	4.34

Note. *** $p < .001$, ** $p < .01$, * $p < .05$.

Table A2 presents the findings from the final model for middle school students. School-level predictors the average percentages of Free and Reduced Lunch (p=0.93) and Title I status of the school (p=0.98) were not significant predictors. Completion of at least 8 skills in Exact Path emerged as a significant positive predictor ($p < 0.01$), suggesting a correlation between consistent use of the intervention and enhanced Math performance for middle school students. Students with Individual Education Plans, English Learners, and Hispanic (ethnicity) students generally exhibited lower Math achievement than their peers. Black students, on average, received lower Spring test scores ($p < 0.001$). Although some racial groups were not statistically significant predictors, they were included in the final model due to the baseline differences of racial groups falling between 0.05 and 0.25 (What Works Clearinghouse, 2022). There are no Pacific Islander students in the matched sample for middle school students.

Table B2

Two-level Hierarchical Linear Regression Model for Middle School Students (N=626)

Variable	Coefficient	SE
Intercept	286.04***	23.22
Intervention	18.92**	6.80

Fall	0.65***	0.03
IEP	-35.64***	8.11
EL	-42.11**	15.47
Hispanic (Ethnicity)	-11.91*	6.13
Native American	-40.61	30.05
Two or More Races	-9.41	14.18
Asian	18.02	24.88
Black	-33.83***	7.83

Note. *** $p < .001$, ** $p < .01$, * $p < .05$.