Evaluation of a Math Intervention Program Implemented with Community Support

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Abstract

Evidence-based interventions exist for improving multiple fundamental math competencies, but delivering interventions with fidelity and within a data-driven tiered framework is a practical challenge faced by most schools. The current study evaluated a math intervention program delivered with community-based resources via AmeriCorps. At the beginning of the school year, students in grades four through eight (N = 550) were randomly assigned to receive math support via the program or to a waitlist control group. Outcomes were measured with a broad-based assessment of math achievement in the winter. Results from intent-to-treat analyses showed a significant and positive effect (d = .17) for the program that increased slightly under optimal dosage conditions (d = .24). The observed results extend existing literature on math interventions in schools by illustrating the potential for partnerships between community-based organizations and schools to improve outcomes for at-risk students.

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The development of fundamental math competencies is both inherently valuable and predictive of future educational milestones (National Mathematics Advisory Panel, 2008). Young children who demonstrate low math performance are at greater risk for math problems in middle school (Morgan, Farkas, Hillemeier, & Maczuga, 2016; Watts, Duncan, Siegler, & Davis-Kean, 2014), whereas stronger math achievement earlier in school provides a foundation for future success (Torbeyns, Schnieder, Xin, & Siegler, 2015; Wang & Goldschmidt, 2003). Students with strong fundamental math competencies are better prepared to take and succeed in advanced math courses, which in turn increases their likelihood to complete high school and attend college as well as pursue higher-paying science, technology, engineering, and mathematics professions (Adelmann, 2006; Long, Conger, & Latarola, 2012; Spielhagen, 2006; VanLeuvan, 2004).

Early math competencies related to later success and achievement have been identified via longitudinal research (Hansen et al., 2014; Siegler et al., 2012). Among all math competencies, an ability to work effectively with whole and rational numbers by late elementary and middle school appears to be particularly important (National Mathematics Advisory Panel, 2008). This is likely because students draw on their understanding of how to work with whole and rational numbers as a basis for much of their future math learning. For example, whole and rational number competencies support division and working with fractions (Siegler et al., 2012). Such predictive relationships with later mathematics achievement appear to be weaker for other mathematical competencies such as geometry and measurement (Nguyen et al., 2017).

Research suggests that knowledge about the degree to which fundamental competencies contribute to future math successes could be better used to inform implementation of math intervention programs. Long-term trends in national performance show that fewer than 40% of fourth and eighth grade students were at or above benchmarks for grade-level proficiency on the National Assessment of Educational Progress, and overall performance in both grades trended downward for the first time in over two decades (National Center for Education Statistics [NCES], 2016). Moreover, demographic factors such as ethnicity, gender, and socioeconomic status (SES) are all associated with math outcomes (Tate, 1997), in that math performance for non-white, female, and impoverished students tends to be further depressed for these subgroups relative to their white, male, and socioeconomically advantaged peers (NCES, 2016).

Schools often struggle to provide access to high-quality instructional experiences that meet student needs (Bradley, Corwyn, McAdoo, & Coll, 2003; Crosnoe et al., 2010; Hamre & Pianta, 2005), and implementing intervention programs to improve fundamental math competencies may be particularly challenging for educators. In addition to barriers to implementing educational interventions such as limited staff expertise (see Noell & Gansle, 2016), delivering math interventions is difficult because of pressure to cover the extensive breadth of grade level content within math curricula (Schmidt, Wang, & McKnight, 2005), which is often reinforced with curriculum maps that dictate pacing through the instructional sequence. The result is that despite a clear need to improve the development of fundamental math competencies before they become stumbling blocks to later math success (Gersten et al., 2009; Siegler et al., 2012), many struggling students do not receive the time and depth of instruction necessary to do so (Taylor, 2014). The needs of schools and students suggest that feasible intervention programs are needed to increase the depth and extent of math support for struggling students, but such programs must employ effective instructional practices and demonstrate promise through rigorous research.

Evidence-based Strategies for Developing Fundamental Mathematics Competencies

Intervention programs in education should consist of practices with empirical support for improving a target outcome (Kratochwill & Shernoff, 2004; Riley-Tillman, 2011). In math, empirical support exists for strategies that improve competencies for effectively working with whole and rational numbers (Gersten et al., 2009). In general, such strategies employ the techniques of explicit instruction (Baker, Gersten, & Lee, 2002; Krosenbergen & Van Luit, 2003), which include direct systematic instruction, modeling concepts and procedures, ample opportunities to respond, and corrective feedback (Burns, VanDerHeyden, & Zaslofsky, 2014; Stein, Kinder, Silbert, & Carnine, 2005). Table 1 summarizes three strategies that employ explicit instruction techniques and that were used in the current intervention program.

With the concrete-representational-abstract (CRA) approach, an interventionist improves conceptual understanding by using concrete manipulatives to demonstrate a mathematical concept (e.g., fraction circles to demonstrate equivalency). The interventionist then reinforces understanding of the concept using pictorial representations before introducing the corresponding number-based algorithm (Butler, Miller, Crehan, Babbitt, & Pierce, 2003). Each step of the CRA sequence involves systematic instruction, modeling, and multiple practice opportunities that correspond to abstract and symbolic representations conventionally used in math. Across multiple studies, the CRA approach produced positive results for student understanding and ability to work with fractions (Butler et al., 2003; Carbonneau, Marley, & Selig, 2013; Krosenbergen & Van Luit, 2003), algebra skills (Witzel, Mercer, & Miller, 2003), and for students with learning disabilities (Flores, Hinton, & Strozier, 2014).

The cover-copy-compare (CCC) approach helps students develop stronger computational proficiency via modeling of procedural steps, providing multiple opportunities to respond, and giving immediate feedback (Skinner, McLaughlin, & Logan, 1997). Students typically review a completed multi-digit division problem, cover it, attempt to solve it, and then review their answer for accuracy. The CCC approach has garnered promising evidence as a math intervention (Codding et al., 2007; Joseph et al., 2012), and is supported by theories of math development that suggest efficient computational skills allow students to focus more directly on cognitively complex processes like problem solving and data analysis (Ball et al., 2005). Research indicates that growth in basic computational skills accounts for variation in performance on high-stakes state tests up to grade eight (Nelson, Parker, & Zaslofsky, 2016), suggesting that as computational proficiency improves, students will achieve higher levels of general math proficiency.

Explicit instruction techniques are also featured in intervention strategies for improving the ability to solve word problems. The cognitive strategy instruction (CSI) approach involves scaffolding of self-regulated strategies that teach students to use sequenced, predictable procedures to identify, engage with, estimate solutions for, and ultimately solve various applied word problems (Montague, 1997). For instance, an interventionist would use CSI to help a student solve a word problem for adding two unequal fractions by having them read for understanding, identify the core question, develop a visualization and corresponding hypothesis about the answer, compute the answer using appropriate strategies, and then check their solution. During the intervention, these procedures are explicitly taught and modeled in discrete steps and then students apply the procedures with guidance and feedback, which research indicates can produce large positive effects for students experiencing mathematics difficulties (Zhang & Xin, 2012).

Implementing Math Intervention Programs

Despite promising evidence for specific math intervention approaches that can be used to improve fundamental math competencies, substantial variation has been observed in the degree to which supplemental support in practice mirrors research-based recommendations (Prewett et al., 2012). Schools often face implementation challenges with math intervention programs, such as competing priorities between improving fundamental skills and meeting curricular pacing expectations. Schools may also experience difficulty identifying intervention strategies given that students who struggle with math often struggle with more than one math competency (Jordan, Hanich, & Kaplan, 2003), but much of the evidence base focuses on interventions that are narrow in scope with studies that examine a single competency such as computation or ability to solve word problems (see Dennis et al., 2016).

Other logistical barriers likely exacerbate implementation challenges. For example, intervention frameworks like ‘response to intervention’ (RtI) are ubiquitous in educational practice (Jimerson, Burns, & VanDerHeyden, 2016), and have as a core assumption that 15% to 20% of students will require intervention (Fuchs & Vaughn, 2012; Tilly, 2008). In a typical school with 400 students, providing 60-80 students with 80 to 120 minutes of intervention per week—as per the existing evidence-base for math interventions (Gersten et al., 2009)—translates to 54 hours or more of additional support if those students are in groups of three, and exponentially more time if support is provided individually or in schools with substantially greater need. Thus, schools are challenged in identifying defensible intervention programs that are logistically feasible and aligned to student needs.

Implementation difficulties with math intervention programs also appear to extend to data-driven decision making practices. Educators are expected to use data to guide decisions about which students need math intervention as well as the degree to which students respond to the additional support (Lembke, Hampton, & Beyers, 2012); however, research suggests such uses of data are not effectively adopted in practice (Vujnovic et al., 2014). Interpreting data and linking it to instructional decisions is particularly difficult for educators (Van den Bosch, Espin, Chung, & Saab, 2017), and surveys show that fewer than 5% of teachers and school staff understand assessment practices that accompany intervention programs (Castro-Villareal, Rodriguez, & Moore, 2014; Regan, Berkeley, Hughs, & Brady, 2015).

Research indicates that practice-based factors can influence the impact of intervention programs (Forman et al., 2013). For example, a recent national study failed to observe positive effects for RtI intervention programs that were implemented by schools without assistance from researchers or other partners (Balu et al., 2015), despite extensive research on school-based reading interventions that spans decades and includes vast amounts of efficacy evidence (Fuchs & Vaughn, 2012). The national study by Balu et al. (2015) collected self-report implementation data but did not directly measure fidelity and dosage for specific evidence-based intervention strategies, and many schools reported not providing interventions to students who needed them (Fuchs & Fuchs, 2017). Given the knowledge necessary to select evidence-based interventions and the human capital required to ensure implementation is delivered with fidelity (Noell & Gansle, 2016), such findings support the notion that additional capacity and resources may be necessary for schools to effectively implement educational interventions. Math intervention programs should therefore address implementation barriers that are likely to inhibit success.

Implementing Academic Interventions with Community Support

A growing body of evidence indicates that community support can help schools implement educational intervention programs and achieve positive outcomes for students.

Community support refers to individuals and organizations that provide schools with resources, time, and expertise. Several studies have shown that programs implemented with such support produce promising effects. For example, a rigorous review found that instructional support from volunteer tutors produced small but educationally meaningful effects on reading outcomes for treatment students compared to randomly-identified or well-matched controls, and effects were larger when dosage approximated research-based recommendations (Slavin, Lake, Davis, & Madden, 2011). Related research found that interventions using volunteers to provide instructional support produced improvements for reading fluency and comprehension outcomes up to two years later (Burns, Senesac, & Silberglitt, 2008).

Efforts to create a more systematic, scalable approach to the use of community support also appear promising. They often involve connecting schools to organizations that develop a specialization for improving select educational outcomes. For example, an intervention program that used individuals serving in AmeriCorps to train schools' volunteer base in literacy interventions produced small, positive effects on students' reading performance in a large-scale randomized controlled trial (Jacob, Armstrong, Bowden, & Pan, 2016). Such community-supported intervention programs reflect deeper partnerships with schools than traditional volunteer engagement models that typically rely on ad-hoc tutoring in brief after school sessions. Community organizations that focus on the improvement of a specific educational outcome can develop comprehensive expertise and systems for improving that outcome—such as selecting and training individuals to deliver evidence-based interventions and using data-driven practices—which serve to complement and extend existing school capacity. Moreover, cost analyses suggest that expenses to schools can be considerably lower with such community-school partnerships than other programs that require schools to take on sole responsibility for managing implementation of programs with individual tutors (Hollands et al., 2016).

Community-supported intervention programs that focus on student needs within a school system are conceptually aligned with recommendations to consider a student's broader ecology when addressing learning difficulties (Reschly & Christenson, 2012), and incorporate an ecological perspective by involving more than one system in a student's developmental context. Yet in contrast to conventional ecologically-informed efforts that draw heavily on school resources to coordinate interventions across systems, as occurs with multi-setting behavioral consultation approaches (Sheridan, Bovaird, Glover, Garbacz, & White, 2012), the integration of community-supported intervention programs into a school reflects an alternative application of ecological systems theory (Burns, 2011). In this case, the ecological perspective reinforces the notion that school systems can incorporate resources from other proximal systems, such as local universities or nonprofit organizations as well as national publicly-supported service initiatives (e.g., Corporation for National and Community Service, 2018).

As shown in Figure 1, community organizations have the potential to provide schools with knowledge and resources that, in the case of an intervention program, include the time- and labor-intensive processes of identifying effective strategies, developing accompanying data-driven decision-making practices, and establishing effective implementation protocols. Additionally, community organizations can fill human resource needs for the delivery of the intervention program. Such resources directly address obstacles that serve as barriers to effective intervention delivery. The result is a tangible set of assets that align with core practices of intervention frameworks like response to intervention (Jimerson et al., 2016), and are consistent with calls for concerted efforts to improve student outcomes (Epstein, 1995). To date, empirical research of community-supported intervention programs has focused primarily on literacy, whereas comparable research for math appears nonexistent.

Purpose

The purpose of this study was to evaluate the impact of a school-based, community-supported math intervention program on the academic achievement outcomes of students in grades four through eight. The program provided each partnering school with at least one interventionist to (1) deliver evidence-based concrete-representational-abstract, cover-copy-compare, and cognitive strategy instruction strategies that build student competencies in working with whole and rational numbers; (2) facilitate data-driven decision-making to identify eligible students, target specific math needs, and monitor progress; and (3) ensure implementation fidelity using standard protocols and ongoing coaching. Program interventionists were community members who agreed to a full-time, year-long commitment in AmeriCorps (contact first author for program details). Schools played an active role in the program by having one staff member fully trained in the program who provided ongoing support to the interventionists (see Interventionist training and support section below). This study examined the impact of the program after students had participated in the program for one semester. The following research question guided the study: To what extent does the math performance of students who participated in the community-supported math intervention program for one semester differ from students randomly assigned to a waitlist control condition?

Method

Participants and Setting

The current math intervention program provided support in over 150 schools in Minnesota. Schools were able to participate in the program by submitting an application to the state AmeriCorps office. The application required school principals to agree to implement the program, including the intervention strategies, assessment practices, training and coaching, and time commitment for school staff. The current study occurred in the fall semester of the 2016-2017 school year, and 13 schools in rural (n = 6) and urban (n = 7) settings agreed to participate. On average, 61% of the students at participating schools were eligible for free or reduced-price lunch. At these schools a total of 17 community-based interventionists delivered interventions to students in grades four through eight. Each school was provided a small compensatory stipend for their participation.

Students in the study were selected according to program identification criteria that required students to score below proficiency standards on the prior-year state mathematics assessment and have fall STAR Math scores below STAR Math benchmarks empirically linked to proficiency on the Minnesota Comprehensive Assessment (MCA) state math test. In total, these criteria resulted in 550 students being eligible for the program. All eligible students were randomly assigned into treatment or control group conditions using a simple random number generator in a computer-based spreadsheet program.

Randomization was blocked by school and used an approximate ratio of 60:40 for assignment to treatment and control, resulting in 348 students assigned to treatment and 202 assigned to control. The actual average proportion of students assigned to the treatment group was equal to .63 (*SD* = .11). The randomization procedure was used in all schools, but modest variation in the proportion of treatment assignment was permitted to account for differences in the number of eligible students across schools (i.e., in the case that a school had substantially more or fewer eligible students than expected). Where needed, greater likelihood of assignment to treatment allowed schools to reduce the number of students for whom treatment was withheld (Pocock, 1995).

Students assigned to the treatment group were put into pairs to receive the intervention as per program procedures. Students assigned to the control group were not allowed to receive the program until after the winter post-test, and interventionist logs showed no treatment cross-over. However, students in the control group were allowed to receive other school-based services as normally provided in their school. Surveys sent to school staff to determine the frequency and type of other math supports indicated that both treatment and control group students received supports other than the intervention program, although control group students received other supports more often. Approximately 42% of control group students and 25% of treatment students received 60 weekly minutes of other math support for at least one month of the study duration. Other support typically consisted of semi-structured math activities provided by a school staff member; no evidence-based math strategies such as those used in the current intervention program or from other commercial programs were reported.

The final analytic sample consisted of 489 students, including 310 treatment (10.9% attrition within group) and 179 control (11.4% attrition within group) students. Demographic characteristics for each analytic group are shown in Table 2. The analytic sample included slightly more females than males, and the sample race/ethnicity was approximately 35% White, 28% Black, 20% Asian, 10% Hispanic, and 6% American Indian or Alaskan Native. The distribution of sample characteristics across analytic groups was evaluated using a regression model predicting treatment using pre-test scores, ethnicity, gender, and grade. No variables were significant predictors of treatment condition.

Attrition was primarily due to students not having post-test scores due to a student or interventionist moving or a student being placed in special education. Attrition also included all participating students (12 treatment and nine control) from a single school that withdrew from the study prior to starting intervention. In addition, one treatment case withdrew consent after pre-test data were collected and another was removed due to a STAR Math post-test score outside the plausible range of values (i.e., the observed score was over six standard deviations below the mean). For students missing post-test scores, logistic regression models regressed the presence or absence of post-test data on treatment, demographic data, and pre-test scores. No association was found between treatment assignment or pre-test scores and missing data. With the exception of a potential relationship with ethnicity ($p < .10$ for Asian and Hispanic students), there was also no significant association between missing data and demographic variables.

Measure

The impact on student math skills was assessed using a broad-based measure of math performance. STAR Math (Renaissance Learning, 2013) is a computer-adaptive assessment that can be used with students in grades one through twelve. Scaled scores on STAR Math range from 0-1400. Depending on the age and skill level of a student, a single administration typically requires 20-30 minutes and may include items related to numeration, computation, word problems, geometry, measurement, algebra, estimation, and data analysis and statistics. Reliability in terms of alpha values ranged from .94 to .95 across grades four through eight (Renaissance Learning, 2013). The median correlation for concurrent validity with the MCA, Minnesota's state math accountability assessment, is reported to be .74 across grades and the median predictive validity correlation from fall STAR Math to spring state mathematics test scores is reported to be .71 across three state samples (American Institutes for Research, 2016).

Math Intervention Procedures

Prior to delivering the intervention to students, trained school staff and the community interventionist created student pairs based on comparable STAR Math screening scores and similar performance on a placement test that sampled program content. School staff then scheduled student pairs to receive math support in either two 45-minute sessions or three 30-minute sessions each week for a total of 90 minutes per week. Interventionists delivered all sessions in a quiet location within or near student classrooms.

The intervention program targeted skills involved in working with whole and rational numbers as per expert recommendations for supporting struggling students in grades four through eight (Gersten et al., 2009; NMAP, 2008). For each target skill, interventionists used scripted protocols that applied the concrete-representational-abstract (CRA) strategy to improve conceptual understanding, the cover-copy-compare (CCC) strategy to improve computational proficiency, and cognitive strategy instruction (CSI) to improve word problem solving. The order of the approaches was consistent in that CRA was first, CCC was second, and CSI was last.

Interventionists proceeded between intervention approaches for a target skill only after students demonstrated successful performance on brief and informal ‘mastery checks’, which were designed to help interventionists progress through content according to expert recommendations (Gersten et al., 2009). Mastery checks consisted of one to three items that took approximately 5 minutes to administer and assessed student performance on components of each skill that were targeted by each of the respective intervention strategies. For example, after receiving intervention with the CRA strategy and demonstrating sufficient understanding of multi-digit multiplication on the corresponding mastery assessment, the interventionist proceeded with the CCC strategy for multi-digit multiplication.

After receiving intervention with all approaches for a given subskill (e.g., CRA, CCC, and CSI all targeting multi-digit multiplication), students completed a comprehensive formative assessment covering each aspect of the subskill that included approximately 8-15 items and took approximately 15 minutes to complete. If students failed to master any aspect of the subskill on the comprehensive formative assessment, interventionists provided a remedial lesson until students demonstrated accuracy on the mastery check; comprehensive formative assessments were not provided twice. After students completed the remedial lesson and were successful on the informal mastery check, intervention continued to the next skill in the sequence (e.g., double-digit division).

Interventionist training and support. As noted previously, interventionists were serving their communities as part of an AmeirCorps program. In this program, the interventionists dedicated their service commitment toward implementing math interventions in schools. The AmeriCorps program worked in partnership with the schools to recruit interventionists from each school's local community. Interventionists were then trained on all program components during a centralized 4-day in-person training led by program trainers with doctoral degrees and experience conducting math intervention and assessment research. Training included both didactic and active learning components and covered topics such as intervention delivery, data-based decision making, and an overview of relevant research. Interventionists also participated in two additional professional development trainings lasting two hours each that were held one and two months following the initial training. In the additional trainings, interventionists were provided with professional development to strengthen their understanding and skills with data-based decision-making, behavior management, and goal setting.

The intervention program required each school to identify a staff member to be fully trained in program components. This person was typically a math interventionist, but was sometimes an assistant principal or math teacher with sufficient time for working with the intervention program. School staff members supported the interventionist with logistic details related to incorporating the program into the school (e.g., scheduling students; identifying appropriate intervention space near student classrooms), and also provided coaching observations at least monthly. School staff members spent between 6 and 9 hours per month on these activities throughout the school year.

Each school's staff member and interventionist were supported by an external coach who was contracted by the intervention program to provide additional onsite support 1-2 hours per month. All program personnel attended the same trainings to ensure interventionists, school staff, and external coaches understood the core expectations for the program. As per program guidelines, a minimum of nine coaching sessions were provided throughout the year, with more sessions (i.e., up to eight) in the fall of the school year than in the spring (i.e., up to three). All coaching sessions included an observation of the intervention using a fidelity checklist, feedback designed to improve or maintain high levels of intervention fidelity, a review of student data, assistance in data-based decision-making, and general support.

Fidelity of implementation. The fidelity checklist used by coaches in the intervention program consisted of the steps to accurately implement the intervention in accordance with its evidence base (e.g., interventionists follow a specific protocol to model conceptual ideas for adding fractions). Completed fidelity checklists were then scored as a percentage of total correctly implemented steps out of the overall total steps. During the current study, which occurred in the first half of the school year, the 17 interventionists involved in the evaluation were observed by coaches between five and eight times with an average of 6.6 observations per interventionist. Interventionist fidelity during these observations ranged from 74% to 100% (*M* = 94%).

Analysis Procedures

To evaluate the extent to which students assigned to the math intervention program demonstrated improved math scores relative to those assigned to the control group, we fit two models to the STAR Math post-test data: an intent-to-treat (ITT) model and an Optimal Dosage (OD) model. The main model was an ITT analysis and included all students assigned to receive intervention. The OD model only included students who received the intervention at an optimal dosage level. Specifically, students were included in the OD group if they received at least 12 weeks of intervention and at least 60 minutes of support per week, which was determined as a conservative criterion for adequate intervention program dosage based on guidance from research and practitioners (Gersten et al., 2009). Approximately 36% of students originally assigned to the treatment group were removed for the OD analysis (see Table 2 for demographic distributions). The control group in both analytic models was identical.

In both analytic models, students' post-test STAR Math scores were regressed on treatment assignment and pre-test STAR Math scores. Given that students were nested within 12 schools in the final analytic sample, 11 dummy coded variables were also included in both models to control for school effects. The addition of those variables was particularly relevant as there were differences across schools in the average level of dosage. As shown in Table 3, half of the 12 participating schools had average levels of dosage that fell below expectations on one or more metric of intervention dosage, although four were very close (less than one week or minute, on average) to meeting expectations. The resulting model for final analyses had the following form:

(1) $$Y_i = \gamma_0 + \sum_{p=1}^{n} \gamma_{ip} X_p + \gamma_{it} X_t + \varepsilon_i$$

where *Yi* is a vector of integer outcomes reflecting STAR Math post-test scores for the i^{th} (i = 1, 2, … , *n*) student, γ_0 is the intercept, γ_{ip} is a slope capturing the effect of a vector of covariates (X_p) that includes pre-test scores and dummy-coded variables to represent each site, γ_{it} is a dummy coded variable capturing the effect of treatment assignment, and ε_i captures error in post-test scores.

Results

Pre- and post-test descriptive results are displayed across grades and groups in Table 4. As expected, average STAR Math scores tended to increase across grades, which is generally consistent with the scaling of the STAR Math measure. One exception occurred among seventh and eighth grade students in the control group, with eighth grade students scoring slightly lower on average relative to seventh grade students. Average scores also reflected growth from pre- to post-test, which was generally expected as all students received typical instruction in math from their regular teachers during the semester-long study. The average difference between pre- and post-test STAR Math scores was approximately 35 scaled score points for students assigned to the control group, 52 scaled score points for students assigned to the experimental group, and 56 points when examining students in the experimental group meeting OD criteria. Thus, students in the treatment group tended to demonstrate slightly more growth between pre- and post-test.

To evaluate the impact of group assignment on students' post-test scores inferentially, two regression models were fit to the data. Results from the ITT model are presented in Table 5 and indicate that assignment to the math intervention program was associated with a statistically significant and positive effect on students' post-test STAR Math scores, controlling for pre-test scores and schools ($R^2 = .54$, $F(13,488) = 45.54$, $p < .01$). More specifically, assignment to the experimental group in the ITT model was associated with a STAR Math post-test score that was approximately 20.31 scaled score points higher than the control group ($d = 0.17$). Results from the OD model are also presented in Table 5. When restricting the sample to include only students who received optimal intervention dosage, the effect of treatment remained significant ($R^2 = .57$, $F(13, 377) = 38.99$, $p < .01$). In the OD model, assignment to the experimental group was associated with a STAR Math post-test score that was 23.47 scaled score points higher than the control group ($d = .24$).

Discussion

This study evaluated the impact of a community-supported math intervention program that provided schools capacity to deliver evidence-based interventions, assisted in data-driven decision-making practices, and supported implementation of program components. Students who were eligible for the program were randomly assigned to either the program as typically implemented or to a waitlist, and the performance of both groups was analyzed on the STAR Math assessment after one semester. Results showed that students assigned to the program had significantly higher post-test scores than students assigned to the control group and effects were higher for treatment students who received optimal dosage. Researchers suggest that effect sizes of the magnitude observed in this study can have meaningful implications in education when interpreted in the broader context of student age, study rigor, and outcome measure (Hill, Bloom, Black, & Lipsey, 2008). In particular, the current findings were produced in a relatively short period of time (i.e., one semester) and on a broad measure of math performance. Annual normative growth in math, expressed in mean effect sizes, can be used as a benchmark for interpreting the observed effects and ranges from 0.26 to 0.40 for these grades (Lipsey et al., 2012), suggesting an additive impact on students' math improvement comparable to nearly a half grade level of growth.

Implications for Math Intervention Practice

These findings extend existing research regarding the potential for community-based partnerships to substantively contribute to schools' support of at-risk students. Such research has focused mostly on reading (e.g., Jacob et al., 2016; Slavin et al., 2011), but the current study suggests that intervention programs developed and supported by community organizations can complement schools' efforts in math. Positive outcomes for the intervention program, which used community-based interventionists, suggest promise with respect to integrated school-community partnerships to help schools improve student math outcomes. Schools dedicated one staff member to be trained in the program, provide coaching to the interventionist, and assist in data-driven decision-making such as accessing and interpreting student state proficiency data. Although substantive, these activities were relatively modest in comparison to the contribution of the community organization. In addition to the time and effort of the full-time interventionist, the community organization provided coaching and access to STAR Math for data-driven decision-making, which are prescribed practices in intervention frameworks like RtI (see Jimerson et al., 2016). The result was a partnership that involved collaborative functioning of two systems in students' broader developmental contexts, or in terms of ecological systems theory, a mesosystemic alignment (Gutkin, 2012). The successful mesosystemic alignment of community and family resources with school-led intervention efforts has documented success at the individual level across settings (e.g., Sheridan, Bovaird, Glover, Garbacz, & Witte, 2012), but efforts to support system-level needs within schools, such as implementing comprehensive intervention programs, are rare in general (e.g., Jacob et al., 2016) and particularly rare in math.

These findings also have relevance for the broader potential of intervention frameworks like RtI, which presume evidence-based intervention programs are in place for at-risk students. If intervention frameworks are to be successful, an ecological perspective to integrate community systems and resources may be necessary (Burns, 2013). In particular, resources beyond those typically-available to schools may need to be identified. To illustrate from a strictly logistical perspective, the fourth grade math proficiency rate in the state in which this study occurred (Minnesota) was 69% the year of the study. Academic discussions about establishing academic proficiency standards aside, the implication for a typical Minnesota school would be that 31% of students, instead of the assumed 15%-20% from tiered prevention framework literature (Tilly, 2008), need an evidence-based math intervention. Providing each of those students 80-120 minutes of weekly intervention, even in pairs, is a herculean challenge for schools, and adding the time and resources to develop capacity and systems for data-driven decision-making and effective implementation practices (e.g., coaching) further exacerbates the challenge. As demonstrated in this study, there might be promise for schools to augment their internal capacity with both personnel and knowledge resources from their surrounding communities.

Much of the work involved in implementing prevention frameworks lends itself to structured protocols for implementation (Noell & Gansle, 2016), and well-organized community organizations might be able to support schools in establishing and executing those protocols, as demonstrated in related research in reading (Jacob et al., 2016). Doing so could free schools to focus more intently on core instructional practices that offer even greater potential to reduce proportions of at-risk students (Jitendra & Dupuis, 2016). As noted previously in Figure 1, organizations (or multiple organizations) within the community can be tapped to provide content expertise and personnel resources for use within intervention frameworks. In the current study, AmeriCorps was the structure used to procure community-support for schools, and every state has existing AmeriCorps infrastructure, but other resources such as university or corporate partnerships could be viable options as well.

Implications for Understanding Comprehensive Math Interventions

Findings from the present study also have implications for math intervention in general. As discussed, the evidence base is well-established for specific interventions targeting conceptual understanding (Witzel et al., 2003), computational proficiency (Woodward, 2006), and word problem solving interventions (Montague, 1997). Yet existing research on single intervention approaches using researcher-developed measures that closely align with the target skill tends to have a greater likelihood for observing significant effects (Montague, Krawec, Enders, & Dietz, 2014; Zhang & Xin, 2012). The current results suggest that comprehensive math intervention programs can produce meaningful outcomes for struggling students on a relatively broad measure of math performance. Such findings are important because a comprehensive and replicable approach for supporting struggling students is consistent with the goal of intervention frameworks to improve the overall academic health of school systems.

The use of randomization and a relatively large participant sample also overcomes methodological limitations of existing studies of math interventions for competencies related to working with whole and rational numbers. For instance, existing studies that support the use of explicit modeling with concrete and semi-concrete representations had small sample sizes (Butler et al., 2003; Flores, 2010; Witzel et al., 2003), and other notable limitations such as analyzing outcomes at the student level without accounting for potential cluster effects. Studies of interventions to build computational proficiency have relied heavily on single-case designs (e.g., Flores, 2010; Poncy, Skinner, & Jaspers, 2007; Woodward, 2006), which support internal validity but require systematic replications to establish external validity (Horner et al., 2005). The current findings do not isolate the direct benefit of subcomponents of the intervention program, but they do suggest the inclusion of each strategy contributes to effectiveness as part of a comprehensive intervention program, and the ultimate goal of math intervention programs should be to increase broad-based mathematical competence (NMAP, 2008).

Limitations

Although this study used a rigorous design and a relatively large sample to produce evidence that community-supported math intervention programs can support schools in improving student math outcomes, there are several limitations to the findings. Characteristics of the school sample limit the degree to which conclusions are applicable to other settings. The study occurred in schools with a relatively high proportion of students eligible for free or reduced price lunch, and thus findings cannot be extended to schools with relatively low socioeconomic need even though those schools are not devoid of students requiring supplemental support. School-wide socioeconomic status is related to student achievement in that greater socioeconomic need at the school level tends to depress individual student achievement (Perry & McConney, 2010). Thus, identifying effective community-supported math intervention programs holds promise for schools in community settings that have higher economic need, but further research is necessary to understand the promise of the program in other socioeconomic settings.

A separate limitation is that the comprehensive nature of the intervention program—inclusive of multiple evidence-based interventions, data-driven decision-making, and implementation support—prevents understanding of the degree to which any single component, or subcomponent, contributed to student outcomes. Research adopting novel methodologies designed to evaluate the value of modular interventions (e.g., Baker et al., 2017) might help determine the most effective or efficient components of comprehensive intervention programs. With third graders, for instance, word problem solving interventions provided a stronger impact on proximal and distal measures of pre-algebraic skills than did calculation interventions (Fuchs et al., 2014); other research suggests that student growth in simple math facts continues to contribute to overall math competency through middle school (Nelson et al., 2016).

Other limitations concern school buy-in for the program. The degree of principal and teacher buy-in was unknown. Many schools reapply for the program on an annual basis suggesting a minimal level of implementer buy-in, but other aspects of buy-in may be related to intervention program outcomes. Implementer perceptions of need, understanding of program benefits, and belief in obtainable outcomes were associated with stronger implementation in research that identified a relationship between implementation and program outcomes (Durlak & DuPre, 2008). This issue may be particularly relevant for interpreting the OD results, given that the current study was unable to control for buy-in variables that could confound the finding that receiving a minimal level of dosage appeared to confer additional benefit. Relatedly, program costs have not been subjected to rigorous cost-effectiveness research (e.g., Jacob et al., 2016), and therefore costs per student are largely unknown. Such work would help inform the scalability of the current program as a factor stakeholders consider when determining buy-in.

A last set of limitations pertains to the methodological characteristics of the study. There was a relatively high level of missing data (11%) for a study of this length, which is known to potentially bias outcomes. Differential attrition was trivial and only marginally related to demographic characteristics (only potentially related to Asian and Hispanic ethnicities), and when differential attrition is low even relatively high overall attrition minimally biases estimates (What Works Clearinghouse, 2017), but biased estimates remain a possibility. The study also was limited with respect to measuring impact on other variables related to math performance. A single outcome was measured, which was broad-based, comprehensive and predictive of state math proficiency outcomes (Renaissance Learning, 2015), but measuring other math outcomes, such as math computation or word problem solving, would strengthen understanding of the program's effects as well as permit analyses of the relative role of math subskills in overall math competency.

Conclusion

Despite its limitations, the current study suggests that community-supported math intervention programs hold promise in late elementary and middle school. Given the challenges schools face in implementing intervention programs (Vujnovic et al., 2014), combined with the need of their students (NCES, 2016), effective support from communities may be a valuable and relatively untapped asset to reverse disappointing and longstanding trends in student performance. Ongoing research that strengthens the understanding and impact of such an approach appears warranted.

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Table 1.

Summary of Strategies used within Intervention Program

	Concrete Representational Abstract (CRA)	Cover Copy Compare (CCC)	Cognitive Strategy Instruction (CSI)
Skill Progression	First	Second	Third
Skill focus	Conceptual Understanding	Computational Proficiency	Word Problem Solving
Description	Intervention scaffolds students' understanding by using progressive representations of a given math concept, such as 3D manipulatives (e.g., base-10 blocks), 2D illustrations (e.g., area model), and symbols (e.g., numerals).	Intervention strengthens students' computation skills through modeling procedural steps, providing multiple opportunities to respond, and giving immediate feedback.	Intervention develops students' self-regulator problem solving using a 7-step process that teaches sequenced, predictable procedures to identify, engage with, estimate solutions for, and ultimately solve various applied word problems.
Materials	Manipulatives, illustrations, symbols	CCC worksheet	7-step process list
Representative Research	Carbonneau, Marley, & Selig (2013)	Joseph et al. (2012)	Zhang & Xin (2012)

Table 2.

Demographic Distribution across Groups

Demographics	Full Sample	ITT Analytic Sample		OD Analytic Sample	
	(n = 550)	Control (n = 179)	Experimental (n = 310)	Control (n = 179)	Experimental (n = 199)
Gender					
Male	48.4%	49.8%	51.0%	49.8%	53.3%
Female	51.6%	50.2%	49.0%	50.2%	46.7%
Ethnicity					
White	34.6%	35.2%	35.2%	35.2%	39.7%
Black	27.9%	25.7%	29.0%	25.7%	28.6%
Asian	20.0%	18.4%	21.6%	18.4%	17.1%
Hispanic	10.3%	12.8%	7.7%	12.8%	9.0%
Am. Indian/ Alaskan Nat.	6.0%	1.7%	5.2%	1.7%	4.5%
Nat. HI or Pacific Islander	0.1%	0.0%	0.3%	0.0%	0.5%
Multi-Racial	1.0%	1.7%	1.0%	1.7%	0.5%
Grade					
Four	21.1%	20.2%	21.3%	20.2%	22.6%
Five	13.7%	10.8%	15.5%	10.8%	16.6%
Six	22.4%	26.1%	22.3%	26.1%	21.6%
Seven	19.7%	20.2%	18.7%	20.2%	13.6%
Eight	23.1%	22.7%	22.3%	22.7%	25.6%

Note: ITT = Intent to Treat; OD = Optimal Dosage

Table 3.

Characteristics of Implementation across Participating Sites

		Weeks of Tutoring		Minutes/Week	
Sites	Students	*M*	*SD*	*M*	*SD*
Site A*	24	11.04	4.39	72.37	28.17
Site B*	39	11.77	4.63	56.86	16.47
Site C*	90	11.88	4.29	65.17	11.87
Site D*	27	11.89	3.23	67.61	15.80
Site E*	12	16.08	2.11	59.05	7.37
Site F*	12	17.83	0.58	59.31	4.74
Site G	10	14.90	1.20	69.67	3.36
Site H	23	15.65	1.11	68.41	5.86
Site I	11	16.00	0.00	63.49	4.62
Site J	24	16.58	1.25	67.91	4.47
Site K	16	16.63	1.82	63.77	5.17
Site L	22	18.14	4.05	64.27	6.63
All Sites	310	14.68	3.64	65.90	10.80

* Denotes sites at which one of the average values fell below criteria used to determine optimal dosage (OD) of 12 or more weeks and 60 minutes per week or more.

Table 4.

STAR Math Performance across Groups and Occasions

Grade	Control Group			ITT Treatment Group			OD Treatment Group		
		Pre-Test	Post-Test		Pre-Test	Post-Test		Pre-Test	Post-Test
	N	*M* *(SD)*	*M* *(SD)*	*N*	*M* *(SD)*	*M* *(SD)*	*N*	*M* *(SD)*	*M* *(SD)*
4	41	532.37 (48.31)	575.44 (54.61)	66	535.33 (49.95)	601.20 (70.62)	45	535.27 (47.21)	612.09 (69.65)
5	20	609.55 (60.77)	673.00 (63.63)	48	609.79 (67.42)	670.85 (87.84)	33	622.94 (57.19)	688.15 (83.05)
6	40	663.70 (53.78)	695.92 (88.41)	69	662.19 (53.60)	707.55 (70.21)	43	661.28 (51.37)	730.40 (53.44)
7	36	714.11 (61.54)	741.08 (83.92)	58	688.09 (68.53)	736.81 (71.48)	27	684.04 (64.88)	718.85 (72.73)
8	42	694.45 (81.75)	717.19 (81.39)	69	715.77 (85.75)	759.43 (75.96)	51	729.82 (65.37)	760.67 (81.53)
All Grades	179	644.92 (92.31)	679.84 (96.89)	310	643.84 (92.87)	696.25 (93.69)	199	647.08 (90.26)	702.83 (90.22)

Note: ITT = Intent to Treat; OD = Optimal Dosage (12 or more weeks and 60 or more minutes per week of tutoring)

Table 5.

Regression Results for Intent-to-Treat and Optimal Dosage Models

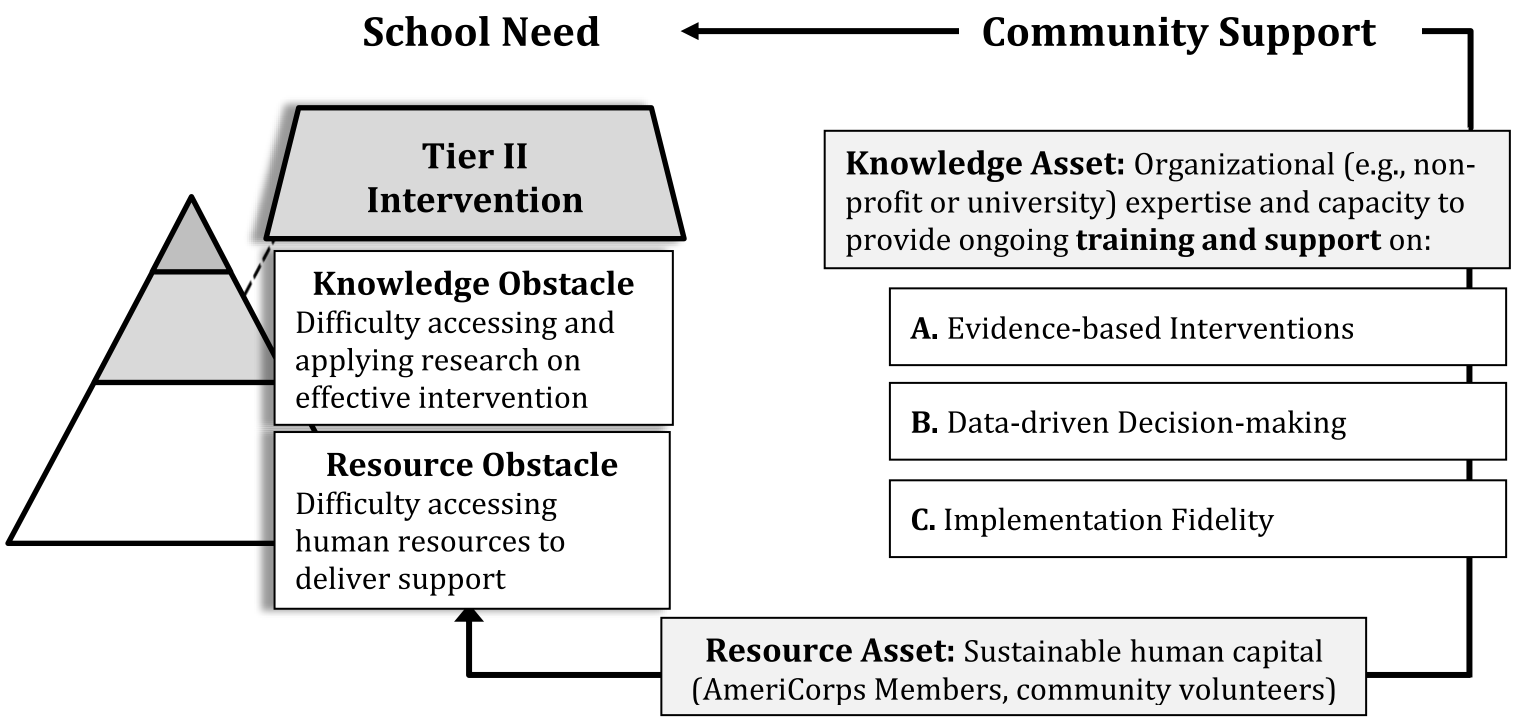
Effect	*b*	SE(*b*)	*t*-value	*p*-value
Intent-to-Treat (*n* = 490)				
Intercept	355.30	30.85	11.52	<0.01
Pre-Score	0.54	0.04	12.61	<0.01
Treatment[a]	20.31	6.18	3.29	<0.01
Site A	-96.53	12.34	-7.82	<0.01
Site B	-17.34	12.18	-1.42	0.71
Site C	-55.72	13.21	-4.22	<0.01
Site D	27.74	12.01	2.31	<0.05
Site E	-65.28	16.64	-3.92	<0.01
Site F	-6.87	15.03	-0.46	1.00
Site G	-14.64	12.52	-1.17	0.49
Site H	-45.51	19.29	-2.36	<0.05
Site I	-52.50	13.24	-3.97	<0.01
Site J	-29.38	10.88	-2.70	<0.01
Site K	-73.45	17.85	-4.12	<0.01
Optimal Dosage (*n* = 378)				
Intercept	317.33	35.96	8.82	<0.01
Pre-Score	0.59	0.05	11.72	<0.01
Treatment[b]	23.47	6.58	3.56	<0.01
Site A	-88.54	13.00	-6.81	<0.01
Site B	-4.88	13.09	-0.37	0.71
Site C	-43.87	14.46	-3.03	<0.01
Site D	32.90	12.42	2.65	<0.05
Site E	-30.35	19.64	-1.55	0.12
Site F	0.05	15.33	0.00	1.00
Site G	-8.97	13.06	-0.69	0.49
Site H	-35.36	20.15	-1.76	0.08
Site I	-37.96	14.98	-2.53	<0.05
Site J	1.36	13.59	0.10	0.92
Site K	-80.29	27.03	-2.97	<0.01

[a]Intent-to-treat treatment sample size = 310

[b]Optimal dosage treatment sample size = 199

Note. Treatment 1 = yes, 0 = no; Site L was the reference site.

Figure 1. Heuristic for a systems-level school-community partnership within a tiered intervention framework.



Note. Intervention frameworks are commonly referred to as 'response to intervention' or 'multi-tiered systems of support.' Within these frameworks, 'Tier II' is a core element that calls for provision of interventions and the use of data to remediate skill deficits and prevent need for more intensive support (i.e., special education).