Research Article

Psychological Science
2022, Vol. 33(7) 1086–1096

DOI: 10.1177/09567976211061109
www.psychologicalscience.org/PS
SAGE

Growth-Mindset Intervention Delivered by Teachers Boosts Achievement in Early Adolescence

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Abstract

School underachievement is a persistent problem in the United States. Direct-to-student, computer-delivered growth-mindset interventions have shown promise as a way to improve achievement for students at risk of failing in school; however, these interventions benefit only students who happen to be in classrooms that support growth-mindset beliefs. Here, we tested a teacher-delivered growth-mindset intervention for U.S. adolescents in Grades 6 and 7 that was designed to both impart growth-mindset beliefs and create a supportive classroom environment where those beliefs could flourish (N = 1,996 students, N = 50 teachers). The intervention improved the grades of struggling students in the target class by 0.27 standard deviations, or 2.81 grade percentage points. The effects were largest for students whose teachers endorsed fixed mindsets before the intervention. This large-scale, randomized controlled trial demonstrates that growth-mindset interventions can produce gains when delivered by teachers.

Keywords

academic achievement, adolescent development, motivation, growth mindset, affordances, open data

Received 5/4/21; Revision accepted 10/21/21

One in five students in the United States will not earn a high school diploma on time (McFarland et al., 2018), and 65% will not earn a bachelor's degree (Snyder et al., 2019). Lower levels of education put these individuals at greater risk of unemployment, poverty, and poor health (Autor, 2014; Patton et al., 2016).

For many students, academic struggles begin during early adolescence and persist (Barber & Olsen, 2004; Eccles et al., 1993). Students who fall behind in middle school are more likely to drop out of high school (Bowers, 2010). Here, we tested an intervention to help middle school students stay on track academically. The intervention sought to cultivate a growth mindset about intelligence, the belief that intellectual abilities can be improved through effort and learning. As students embrace a growth mindset, they take advantage of more learning opportunities and become more resilient in the face of academic setbacks (Blackwell et al., 2007).

Direct-to-student, computer-based growth-mindset interventions improve struggling students' grades. In a recent nationally representative study of ninth graders in the United States (Yeager et al., 2019), a brief computer-based growth-mindset intervention increased the grade point average of lower achieving students by 0.11 standard deviations, a noteworthy effect size relative to benchmarks in other large school-based experiments (Kraft, 2020). Positive effects have been replicated with diverse students (Broda et al., 2018; Paunesku et al., 2015).

Correction (August 2023): The Preregistered badge was removed from this article. See https://doi.org/10.1177/00031224231176323 for the corrigendum.

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However, the benefits of direct-to-student, computer-based growth-mindset interventions depend on the classroom environments in which students find themselves. In Yeager and colleagues' (2022) nationally representative study, the intervention raised the math grades only of students who happened to have a math teacher with a growth mindset, presumably because math teachers with fixed mindsets undermined the treatment effect. This suggests that, to be maximally effective, interventions require contexts with *psychological affordances* that permit the adaptive perspective the intervention seeks to instill (Walton & Yeager, 2020; Yeager et al., 2022).

The intervention tested here (*Brainology*) was designed to provide such psychological affordances in two ways. First, it gave teachers a prominent role in delivering the intervention. This conveys to students that teachers endorse a growth mindset and believe students can improve. Teachers delivered three of every four lessons in Brainology and led students in actively processing the material. For example, teachers might ask students to identify subjects where they wanted to improve and help them design a plan for maximizing their learning in those subjects, demonstrating the concept of malleable intelligence.

Second, ongoing support was provided to teachers to ensure that the mindset message was communicated with high fidelity. Misconceptions about what a growth mindset is and how to teach it have spread as growth mindsets have become popular with educators (Sun, 2018, 2019). Indeed, lack of ongoing implementation support may help explain why a recent large-scale test of a teacher-delivered growth-mindset intervention in the UK failed to benefit students (Foliano et al., 2019)—although the intervention provided one training session and an implementation guide, lack of continued support may have allowed teachers' actions and words to inadvertently drift from the growth-mindset message and weakened its effects (Sun, 2018, 2019). In the current study, teachers were given a curriculum guide, video-based resources, in-person training, and pedagogical techniques for communicating growth mindsets to students. In addition, staff with expertise in growth mindsets and teaching observed Brainology lessons regularly and provided coaching throughout the intervention.

In summary, although ours is not the only large-scale randomized controlled trial (RCT) of a mindset intervention, it has a distinctive feature that advances scientific understanding about the effects of these interventions: The present RCT is the first large-scale test of a teacher-delivered growth-mindset intervention that provided ongoing implementation support to teachers. If effective, this would be the first large-scale RCT to demonstrate that teacher-delivered growth-mindset interventions can benefit students.

Statement of Relevance

School underachievement diminishes the well-being and health of many students in the United States. Computer-based growth-mindset interventions, which teach students that intelligence is malleable, have benefited students who are struggling but only when those students happen to be in classroom environments that support growth-mindset beliefs. Here, we found for the first time that a teacher-delivered growth-mindset intervention enhances the real-world grades of struggling early adolescents and changes teachers' mindset beliefs in the process. This large-scale, randomized controlled trial demonstrates that growth-mindset interventions can produce gains when delivered by teachers.

We had three primary questions about the effects of the intervention. First, we investigated whether Brainology improved grades only in Brainology classrooms or whether there were spillover effects in other classrooms as well. We might expect spillover effects because prior direct-to-student interventions have raised grades in multiple subjects (Paunesku et al., 2015; Yeager et al., 2019). Yet by involving teachers, Brainology was designed to both instill growth mindsets and provide a growth-affording context. Therefore, we might see the largest gains in Brainology classrooms because this is where students receive the full intervention package (beliefs plus context).

Second, we investigated whether Brainology increased the grades of lower achieving students most. We defined lower achieving students as those who had lower preintervention grades than others in the sample; we tested this by using the full spectrum of preintervention grades and computing marginal tests at ±1 standard deviation of preintervention grades. This analysis was informed by findings that lower achieving students benefit most from growth-mindset interventions (Paunesku et al., 2015; Yeager et al., 2019).

Third, we investigated whether the effects varied by teachers' preintervention mindsets. We might expect the strongest effects in classrooms where teachers initially endorsed growth mindsets because these teachers could be more enthusiastic and effective at teaching the program. Conversely, the effects could be strongest in classrooms where teachers start with a fixed mindset because their students have the most to gain from changes in the classroom context. That is, the intervention may

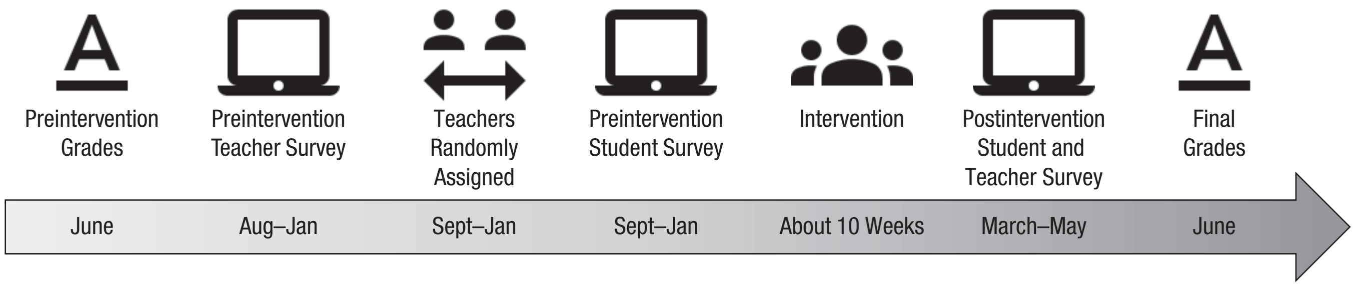

Fig. 1. Timeline of data collection. The month of random assignment and pre- and postintervention survey administration varied by school.

compensate for the negative toll that teachers with fixed mindsets typically take on students' motivation and achievement (Canning et al., 2019; Heyder et al., 2020). Finally, we explored the possibility that both preintervention achievement and preintervention teacher mindsets might compound the effects of the program given that cumulative risks have exponential consequences (Evans et al., 2013) and an intervention addressing multiple risks might have exponential benefits.

Method

Overview

Participants were 52 sixth- and seventh-grade teachers and their students from city schools on the East and West coasts of the United States. Each teacher was randomly assigned to either the Brainology condition or the no-treatment control condition. The teacher analytic sample ranged from 48 to 50, and the student analytic sample from 1,838 to 1,996, depending on the analysis. Brainology was delivered during core English, math, or science classes. Final report-card grades were collected from the previous and concurrent school years, and surveys assessing growth mindsets were administered before and after the intervention (Fig. 1). Data, analysis code, and a copy of the preregistration are available at https://osf.io/z2nvy/.

Participants

Teachers from 12 middle schools located in cities on the East and West coasts of the United States were recruited through email and mail outreach, site visits, and presentations at school meetings. Eligible participants for Cohorts 1 and 2 were core science teachers who (a) did not have extensive exposure to growth-mindset curricula or books, (b) were working at schools where at least two teachers were willing to participate, and (c) were located close enough to receive on-site visits from implementation staff. Initially, science teachers were targeted because Brainology teaches basic neuroscience that integrates well with science content. Because of recruitment challenges for Cohort 2, eligibility was broadened for Cohorts 3 and 4 to include core math and English teachers; as before, at least two teachers of the same subject needed to be willing to participate. We limited eligibility to core content areas because they are assessed in high-stakes tests and are therefore more consequential for students' academic trajectories.

Teacher sample size was predetermined by a power analysis in *Optimal Design* (Version 3.01; Raudenbush et al., 2011) to detect a minimum average program effect (d) of 0.30 at $p < .05$ with 80% power, while accounting for potential cross-site heterogeneity. The target effect size was informed by prior research (Blackwell et al., 2007). The power calculation indicated that 46 teachers were needed, but recruitment of 60 teachers (14 extra) was targeted to safeguard against attrition. Though 3 years was preregistered, data collection was extended to 4 years to allow more time for recruitment. In Year 4, 52 teachers had been recruited, which provided 80% power to detect an effect (d) of 0.25. Recruitment was terminated at that point rather than extended to reach 60 teachers.

Students reflected the diversity of young people in their school districts: District records indicated that 56% were Latinx, 15% were Black, 14% were White, 12% were Asian, and 3% were of another ethnicity. Approximately 72% of students were eligible for free or reduced-price lunch (4% of students, n = 99, were missing this indicator because one school district did not provide access to these data). Teachers were racially and ethnically diverse as well: 40% White, 19% Latinx, 14% mixed race or ethnicity, 10% Black, 6% Asian, and 6% other ethnicity; three teachers declined to provide this information. Teachers had between 0 (i.e., they were in their first year) and 37 years of experience teaching middle school (M = 11.03, SD = 8.19, Mdn = 9).

Students and teachers in the intervention and control groups were balanced on preintervention mindset (growth vs. fixed), grades, and most characteristics, although the intervention group had fewer seventh-grade students than the control group ($g = -0.21$, $p < .001$; see Tables S4–S9 in the Supplemental Material available online).

Procedure

Data collection. As seen in Figure 1, final report-card grades were collected from school district records for the previous and concurrent school years. Surveys assessing students' growth mindsets were administered online during a typical class session in the control and intervention groups before the intervention began and within a few weeks after its completion. Surveys assessing teacher mindsets were administered online before the first teacher training and after the intervention.

All teachers remained in the study for its entire duration (see Fig. S5 in the Supplemental Material). Two teachers (one control, one intervention) were at a school that did not give grades, and their students were therefore excluded from the analyses on grades. Two teachers (both in the control condition) were missing data on their preintervention mindset, and their students were therefore excluded from the current analyses (see Fig. S5). Results were consistent when the missing data on preintervention teacher mindset were imputed (see robustness checks in the Supplemental Material).

Parental consent was obtained for students through either opt-out or signed forms, depending on school district requirements. In total, 87% of students had consent to participate and provided some data (see Fig. S6 in the Supplemental Material). The average within-cluster response rate for eligible students (i.e., those who had parental consent to participate and did not leave the trial before initial data collection) was 91% for the student survey and 80% for grades. These rates are comparable with those of other large-scale, school-based RCTs (Puma et al., 2009). Outcome attrition at the cluster and individual levels was balanced in the intervention and control groups (see Tables S2 and S3 in the Supplemental Material), and the analytical samples for each model were equivalent before the intervention on participant characteristics, mindsets, and grades (see Tables S4–S9). The institutional review board of the University of California, Davis, approved the project.

Random assignment. An independent, third-party contractor randomly assigned teachers to either the intervention or control condition within school and grade level. Schools provided a list of teachers. The first teacher in the list within strata (i.e., school and grade level) was assigned a number between 0 and 1 via a random-number generator; values between 0 and 0.5 were assigned to the intervention condition, and those between 0.5001 and 1 were assigned to the control condition. Assignment of the remaining teachers within strata alternated between groups, with the control group always following the intervention group, and vice versa.

Intervention and control conditions. Brainology implementation began between October and February depending on the school. As seen in Figure 1, prior to the first Brainology lesson, teachers completed preintervention surveys, and intervention teachers attended an in-person training where they received a curriculum guide with lesson plans, learned about research underlying a growth mindset, and discussed the timeline of research activities. Within approximately 2 weeks of the training, Brainology teachers submitted a personalized intervention plan with deadlines for program milestones. Brainology teachers also had access to online video resources throughout the study.

A description of the intervention and sample lessons are provided in the Supplemental Material. Brainology lessons of between 30 min and 1 hr were administered during regular class sessions across approximately 10 weeks. Implementation staff conducted classroom visits every 1 or 2 weeks to observe implementation, provide feedback, and support teachers. Control teachers taught their classes as usual.

Monitoring and minimizing contamination. We took several steps to monitor and minimize the possibility that Brainology teachers would share the treatment with those in the control group. Early in the recruitment process and throughout the evaluation, we communicated the importance of maintaining the integrity of the randomized design; schools that could not comply with the design were not enrolled in the study. To monitor for potential contamination, implementation staff visited control-group classrooms at least once before and after implementation and approximately once per month during implementation. Brainology was also provided at no cost to those in the control group after the evaluation ended.

Measures

Teachers' and students' growth mindsets were assessed with items by Dweck (1999; e.g., "You have a certain amount of intelligence, and you really can't do much to change it"; reverse coded), rated from 1 (*strongly disagree*) to 5 (*strongly agree*). Teachers' mindsets about failure were assessed with items by Haimovitz and Dweck (2016; e.g., "Experiencing failure facilitates learning and growth"), rated from 1 (*strongly disagree*) to 5 (*strongly agree*). The teacher growth-mindset and failure-mindset measures were correlated (r = .62); therefore, we averaged these measures to create an overall composite of teacher mindsets: Higher values indicated stronger growth beliefs. Findings were nearly identical when we used either the growth-mindset or the failure-mindset items, except that the intervention effect on teacher beliefs was weaker (although directionally consistent) when we used only the failure-mindset items (detailed results, all items, and other measures collected in the study are listed in the Supplemental Material).

Analyses

We used multilevel, mixed-effects regression models to test our predictions; full model equations and detailed data-cleaning procedures are provided in the Supplemental Material. In models examining all grades, the three grades for each participant (English, math, and science) were included as separate data points (Level 1) nested within students (Level 2), within teachers (Level 3), and within schools (Level 4); we did not sum or average participants' grades. In models predicting students' growth mindsets or only one grade, outcomes were nested within students (Level 1), within teachers (Level 2), and within schools (Level 3). Though the preregistration also mentioned nesting within states, we did not end up needing to do so because schools from only two states were recruited. All data were analyzed using intent-to-treat methods.

The models were fitted within a Bayesian framework using the *brms* package (Version 2.14.0, Bürkner, 2017; Stan Development Team, 2021) for R. Bayesian analyses are becoming increasingly common in social science (van de Schoot et al., 2017) given the advantages they offer over conventional frequentist statistics (Wagenmakers et al., 2016). For instance, in contrast to frequentist analyses, Bayesian statistics allow researchers to draw inferences about model parameters in light of the data they have collected, rather than inferences about the *data* given the hypothesis being tested. Thus, the logic of Bayesian statistics is more straightforward and better aligned with the goal of scientific research, which is to assign probabilities to hypotheses, not data. In addition, Bayesian estimation is in sync with recent best-practice recommendations for statistical analysis in social science, which encourage a focus on estimating parameters and their uncertainty rather than significance testing (Amrhein & Greenland, 2018; Gelman & Robert, 2014). Because of these properties, we used Bayesian estimation with weakly informative priors, $n(0, 1)$, to understand the effects of Brainology. Nevertheless, for completeness, we also computed frequentist estimates of the multilevel mixed-effects regression models; their results are in agreement with those of the Bayesian analyses.

All models controlled for preintervention covariates, grade level, gender, race and ethnicity, and class subject. Specifically, models controlled for (a) student- and cluster-level preintervention outcome variables (e.g., growth mindset or grades), centered within cluster or on the grand mean, respectively (Enders & Tofighi, 2007); (b) student and teacher gender; (c) an indicator variable at the student level for Black or Latinx; (d) an indicator variable for sixth grade; and (e) an indicator for class subject (e.g., English, math, or science). To keep the analytic samples consistent, we included preintervention teacher mindsets as a covariate in models where preintervention teacher mindsets were not used as an interaction term.

Complete case analysis was used because it produces unbiased estimates of treatment effects in RCTs when (a) differential outcome attrition is low and (b) there is baseline (preintervention) equivalence in the intervention and control groups in each analytical sample (Puma et al., 2009; What Works Clearinghouse, 2020). These conditions were met in the current study (see Tables S2–S9 and Fig. S7 in the Supplemental Material). Robustness checks that handled missing data in different ways (e.g., dummy variable adjustment, Bayesian multiple imputation) produced consistent results.

For the fixed effects, we used a weakly informative prior: a normal distribution with a mean effect of 0 and a standard deviation of 1, that is, $n(0, 1)$. For the random intercepts, we used half-normal priors with the same standard deviation as that for the fixed effects (Gelman, 2006). A total of four Markov chains, 3,000 iterations, 1,000 burn-in (warm-up) iterations, and a seed of 16 were specified (Bürkner, 2017; Stan Development Team, 2021). Sensitivity analyses using a narrower variance prior for regression coefficients, $n(0, 0.5)$, produced consistent results.

Regression coefficients that correspond to the mean of the posterior distributions and their 95% credible intervals are reported in standard deviations throughout the article to quantify the treatment effects (i.e., the difference between the treatment and control groups). To facilitate interpretation, we also report treatment effects in grade percentage points.

Results

Did the intervention change mindsets?

To test whether the experimental manipulation was successful, we examined the effect of Brainology on student growth mindsets and found the predicted increases. Students who received Brainology had higher growth mindsets at the end of the program relative to those in the control condition (β = 0.34, 95% confidence interval [CI] = [0.26, 0.43]; that is, the intervention increased students'

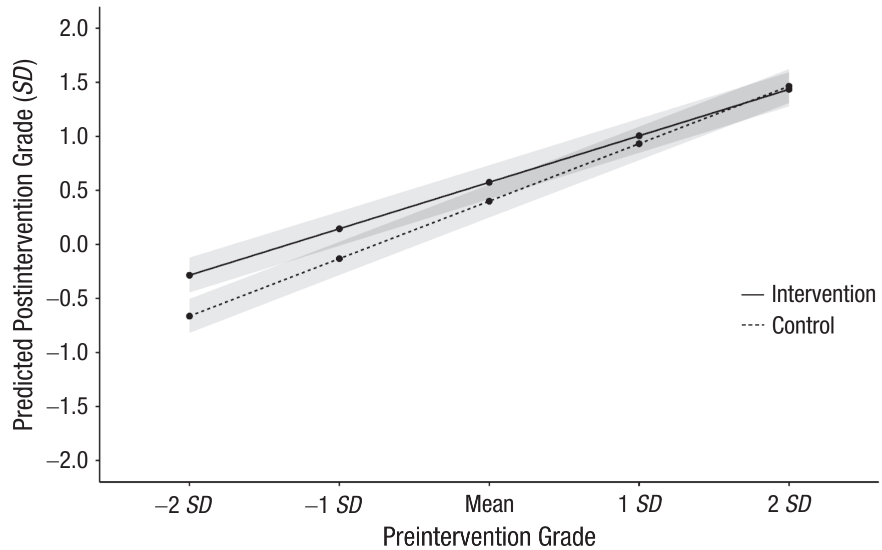

Fig. 2. Predicted postintervention grade as a function of preintervention grade, separately for students in the control and intervention conditions. Shaded regions are 50% credible intervals (i.e., the values between the 25th and 75th percentiles of the posterior distribution).

growth mindsets by 0.34 *SD* relative to the control group). Moreover, teachers' mindsets also changed as a result of delivering the program. Teachers who delivered Brainology had higher growth-mindset beliefs at the end of the intervention compared with those in the control condition (β = 0.70, 95% CI = [0.32, 1.11]).[1] These results suggest that there was little to no contamination of growth-mindset beliefs in the control condition.

Did the intervention boost grades?

Addressing our first question, we found that grades increased in Brainology classrooms more than in other class subjects, as suggested by an Intervention × Classroom (Brainology classroom vs. not) interaction (β = 0.09, 95% CI = [0.04, 0.15]). Unpacking this interaction, we found that students who received the intervention had higher grades than control students at the end of the year in the Brainology class (β = 0.23, 95% CI = [0.07, 0.39]; 2.40 grade percentage points). Estimates of effects in the non-Brainology classes were weaker in magnitude but still potentially meaningful (β = 0.14, 95% CI = [−0.02, 0.30]; 1.46 grade percentage points). The remaining analyses focused on comparing grades in the Brainology class and the control class of the same subject.

Did lower achieving students benefit more from the intervention?

Addressing our second question, we found that effects on grades were strongest for lower achieving students (Intervention × Preintervention Grades interaction: β = −0.12, 95% CI = [−0.20, −0.04]; Fig. 2). As a result of the intervention, grades improved for lower achieving students (β = 0.27, 95% CI = [0.10, 0.44]; 2.81 grade percentage points) more than for those with higher preintervention achievement (β = 0.07, 95% CI = [−0.10, 0.25]; 0.73 grade percentage points; effects estimated at ±1 *SD* of preintervention grades).

Did students whose teachers had fixed mindsets benefit more from the intervention?

Addressing our third question, we found that the effects of Brainology varied by teachers' preintervention mindsets (Intervention × Preintervention Teacher Mindset interaction: β = −0.47, 95% CI = [−0.82, −0.13]). Effects were largest for students whose teachers had stronger fixed-mindset[2] beliefs before the intervention. Students in the intervention group whose teachers had higher preintervention fixed-mindset beliefs ended the year with higher grades than students in the control group whose teachers had higher preintervention fixed-mindset beliefs (β = 0.40, 95% CI = [0.20, 0.60]; 4.16 grade percentage points; effect estimated at −1 *SD* of preintervention teacher mindsets). There was no intervention effect for students whose teachers endorsed more of a growth mindset before the intervention (β = −0.08, 95% CI = [−0.29, 0.13]; effect estimated at +1 *SD* of preintervention teacher mindsets; Fig. 3).

Moreover, having both low preintervention achievement and a teacher with preintervention fixed-mindset beliefs compounded the intervention's benefits. The

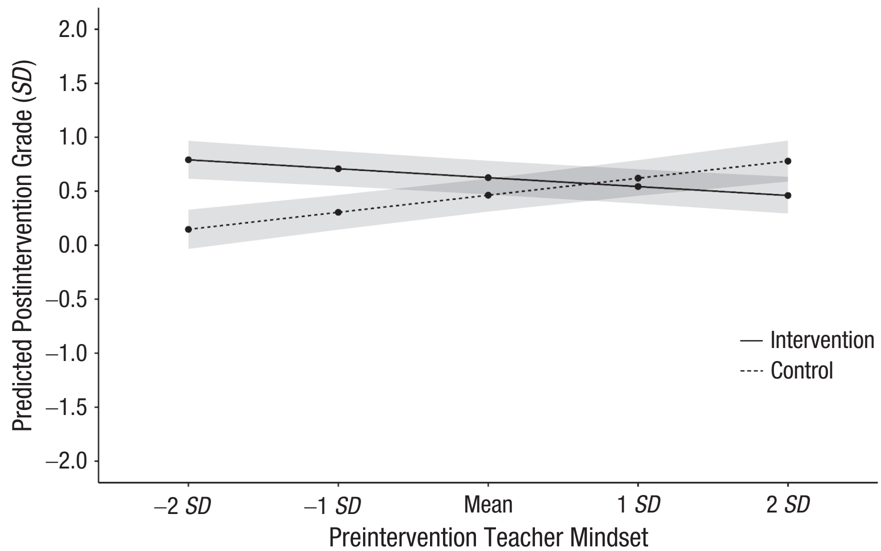

Fig. 3. Predicted postintervention grade as a function of preintervention teacher mindset, separately for participants in the control and intervention conditions. On the *x*-axis, negative values indicate that teachers held more of a fixed mindset before the intervention, whereas positive values indicate that they held more of a growth mindset. Shaded regions are 50% credible intervals (i.e., the values between the 25th and 75th percentiles of the posterior distribution).

effects of Brainology for lower versus higher achieving students varied by teachers' preintervention mindsets (Intervention × Preintervention Grades × Preintervention Teacher Mindsets interaction: β = 0.31, 95% CI = [0.15, 0.48]). Brainology boosted grades for students who had both lower achievement and a teacher with a fixed mindset by 0.63 standard deviations (95% CI = [0.41, 0.84]; 6.56 grade percentage points; Fig. 4). Comparison of the simple effects for all combinations of lower versus higher preintervention achievement and fixed versus growth teacher mindsets showed that lower achieving students whose teachers had fixed mindsets

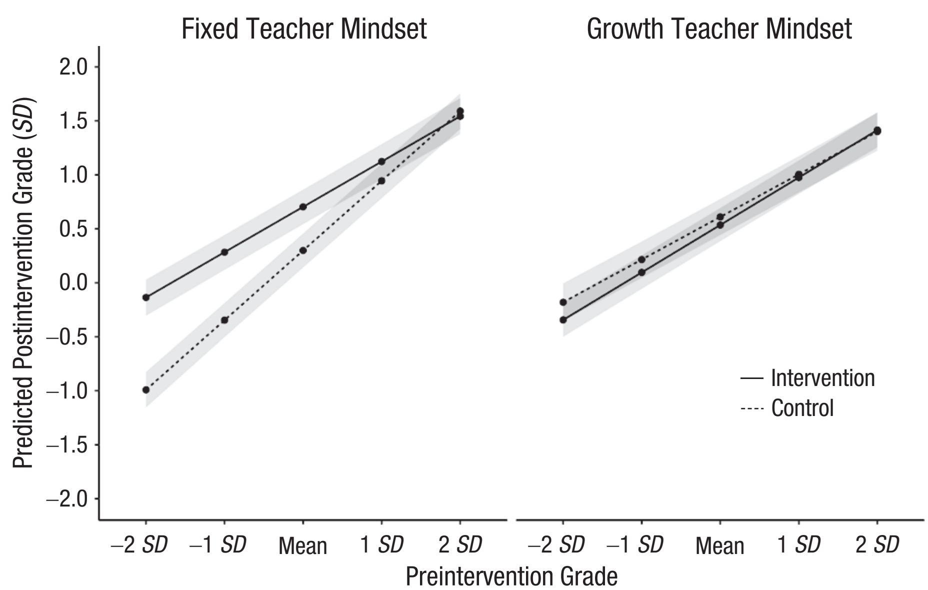

Fig. 4. Predicted postintervention grade as a function of preintervention grade and teacher mindset, separately for participants in the control and intervention conditions. Preintervention growth and fixed teacher mindsets are at ±1 *SD* of the mindsets scale, respectively. Shaded regions are 50% credible intervals (i.e., the values between the 25th and 75th percentiles of the posterior distribution).

had the largest treatment effect of all (see Table S10 in the Supplemental Material). As seen in Figure 4, lower achieving students whose teachers had fixed mindsets were struggling most relative to the other groups, and the intervention brought these students' grades up most.

Robustness checks

The results were consistent across several ways of analyzing the data. Specifically, all of the interaction effects and conditional-average treatment effects were also observed when (a) we used a dummy-variable adjustment (also known as missing-indicator method) for missing preintervention data (Puma et al., 2009); (b) we used Bayesian imputation of missing preintervention grades; (c) we used Bayesian imputation of missing preintervention teacher mindsets; (d) we specified a narrower variance prior for the fixed effects, $n(0, 0.5)$; and (e) we used frequentist estimation in both complete case analysis and with a dummy-variable adjustment for missing preintervention data. See the Supplemental Material for detailed procedures and results.

Discussion

The current RCT showed that a growth-mindset intervention delivered by teachers and supported by implementation coaches increased lower achieving adolescents' grades. The study is the first large-scale RCT to demonstrate that teacher-delivered growth-mindset interventions can be effective.

Brainology improved the grades of lower achieving students in the target class by 0.27 standard deviations. This effect size is noteworthy relative to other large, school-based RCTs that measured effects on real-world achievement (Kraft, 2020). For comparison, recent reviews of school-based RCTs place the mean effect size between 0.06 and 0.16 standard deviations (Cheung & Slavin, 2016; Lortie-Forgues & Inglis, 2019). Effects in the current trial are larger and support using Brainology in schools, which has been a point of controversy in recent discussions of growth-mindset interventions.

The effect sizes also warrant comparison with those of other large-scale growth-mindset interventions. The National Study of Learning Mindsets (Yeager et al., 2019) increased growth-mindset beliefs by 0.33 standard deviations, which is almost identical to our effect size of 0.34 standard deviations. Yet the National Study raised grade point averages for lower achieving students by 0.11 standard deviations compared with an effect of 0.27 standard deviations in Brainology classrooms. This pattern suggests that the two interventions were equally psychologically persuasive but that adding a growth-affording context by involving teachers enhanced improvements in grades (Yeager et al., 2022).

Nonetheless, Brainology's effects should be interpreted in light of the resources that this study required and the characteristics of our sample. Because Brainology was the result of a Department of Education Goal 3 grant, the aim was to implement Brainology under ideal conditions and the teacher-randomized design limited access to in-house support. Under these parameters, providing ongoing, in-person, outside support to teachers was expensive, logistically challenging, and time consuming. This contrasts with computer-delivered direct-to-student interventions, which are less costly. Still, Brainology could be more efficient if outside support were focused on a few in-house school leaders who could provide accountability and resources and help guard against mindset misconceptions.

It is noteworthy that our study was conducted with predominantly low-income racial and ethnic minority students. There is evidence that growth-mindset interventions most benefit students of low socioeconomic status (Sisk et al., 2018) and racial and ethnic minority students (Broda et al., 2018), although other studies have found benefits primarily for lower achieving students regardless of socioeconomic status or race and ethnicity (Paunesku et al., 2015; Yeager et al., 2019). Whether growth-mindset interventions benefit socioeconomically disadvantaged students and students of color more than others needs further research. We also enrolled younger students, who may struggle with independent learning, potentially accentuating the benefits of contextual supports in early compared with later adolescence.

Because our primary outcome was report-card grades, it is important to consider how involving teachers may have influenced grading practices for worse or better. Teachers in our study were not blind to condition, and it is possible that Brainology teachers began grading more leniently to meet a perceived demand and please researchers; this is problematic because it separates grades from learning and risks exaggerating treatment effects. Although we cannot rule out this possibility, we find it unlikely because the treatment effects were not uniform. Rather, the intervention primarily benefited lower achieving students whose teachers started with fixed mindsets. Therefore, to explain the effects, a demand characteristic would have needed to selectively influence how a subset of teachers graded a subset of their students. Moreover, there was evidence that the intervention increased grades outside of Brainology classrooms, which were not subject to demand characteristics.

Another possibility is that involving teachers changed grading for the better. Teachers may have increased formative assessments, allowing students to revise their work and retake tests (Sun, 2019). Additionally, teachers' expectations of students may have shifted as they came to endorse a growth mindset (Rosenthal & Jacobson, 1968). Given that the greatest impact was found for students whose teachers initially had fixed mindsets, it is possible that the program reduced bias in grading. Rather than assigning grades on the basis of low prior expectations, teachers may have more accurately perceived the academic growth of students who were initially lower achieving.

It is notable that Brainology worked primarily for teachers who started the study with fixed mindsets. This finding suggests a compensatory effect wherein the intervention made up for the negative toll that having a teacher with a fixed mindset typically takes on lower achieving students' grades. Yet why were our results different from those of the National Study of Learning Mindsets, which found improvements primarily for growth-mindset teachers (Yeager et al., 2022)? The answer may lie in the unique goals of each intervention. Whereas the National Study's intervention sought only to change students' psychology, Brainology sought to change both students' psychology and the classroom context. Consequently, students could act on growth-mindset beliefs in Brainology classrooms even when their teachers started the year with a fixed mindset, presumably because involving teachers made these classrooms more supportive of a growth mindset. Our finding that teachers' growth mindsets increased as a result of delivering the intervention is consistent with this possibility.

Conclusion

Education provides a pathway toward greater well-being and longevity, but success in school is far from guaranteed. Students' beliefs about their abilities are part of the psychological baggage they carry through school. Here, we showed that a teacher-delivered growth-mindset intervention can enhance the growth mindsets and achievement of adolescents who are struggling and transform teachers' mindsets in the process, setting the stage for greater growth in the future.

Transparency

Action Editor: Eddie Harmon-Jones
Editor: Patricia J. Bauer
Author Contributions

D. Catalán Molina, K. Trzesniewski, L. S. Blackwell, S. Roberts, and T. Porter conceptualized the study. A. Fredericks, A. Cimpian, D. Catalán Molina, K. Trzesniewski, L. S. Blackwell, S. Roberts, and T. Porter designed the methodology. A. Fredericks, D. Catalán Molina, K. Trzesniewski, L. S. Blackwell, S. Roberts, and T. Porter conducted the study. A. Cimpian, D. Catalán Molina, K. Trzesniewski, and T. Porter analyzed the data. K. Trzesniewski and T. Porter drafted the manuscript, and A. Cimpian, A. Fredericks, D. Catalán Molina, L. S. Blackwell, and S. Roberts provided revisions. All the authors approved the final manuscript for submission.

Declaration of Conflicting Interests

L. S. Blackwell is president and cofounder at Mindset Works, which created Brainology, and S. Roberts was director of research. Analyses were conducted by the independent evaluators (T. Porter, D. Catalán Molina, A. Cimpian, and K. Trzesniewski); Mindset Works authors had no access to the data and did not conduct analyses. All other authors declared that they have no potential competing interests with respect to the authorship or publication of this article.

Funding

This research was supported in full by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A150142 to L. S. Blackwell and S. Roberts. The opinions expressed are those of the authors and do not represent the views of the Institute of Education Sciences or the U.S. Department of Education.

Open Practices

All data analysis code have been made publicly available via OSF and can be accessed at https://osf.io/z2nvy/. The design and analysis plans were preregistered at https://sreereg.icpsr.umich.edu/sreereg/pages/sreereg/wwc.html. This article has received the badge for Open Data. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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Acknowledgments

We thank Kristen Budd, Kristin Torrence, Sruthi Jonnalagadda, Joseph Edwards, Natalie Nagpal, Lauren Kiesel, Dana Asby, Zaynah Khan, Pauline Kostopoulos, Anny Fang, Janna Peskett, and Jennifer Poyer for implementation support and Megan Shope, Christian L'Heureux, Lucy Zheng, Chelsea Leslie, Celeste Guzman, Chris Miles, Natalie Ramos, Bruce Randel, and Eric Pape for assistance with research.

Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976211061109

Notes

1. This effect was directionally larger for teachers with fixed mindsets (β = 0.86, 95% CI = [0.32, 1.40]) than teachers with

growth mindsets (β = 0.57, 95% CI = [0.01, 1.11]), estimated at ±1 standard deviation of preintervention teacher mindsets, but the interaction effect was inconclusive (β = −0.27, 95% CI = [−1.12, 0.85]).

2. Teacher mindsets were continuous, and the terms "fixed" and "growth" teacher mindsets refer to those who had lower or higher growth mindsets, respectively, relative to others in the sample.

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