PNAS RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES OPEN ACCESS

A values-aligned intervention fosters growth mindset–supportive teaching and reduces inequality in educational outcomes

Cameron A. Hecht[a,1], Christopher J. Bryan[b,1], and David S. Yeager[a]

Edited by Timothy Wilson, University of Virginia, Charlottesville, VA; received June 24, 2022; accepted April 15, 2023

Group-based educational disparities are smaller in classrooms where teachers express a belief that students can improve their abilities. However, a scalable method for motivating teachers to adopt such growth mindset–supportive teaching practices has remained elusive. In part, this is because teachers often already face overwhelming demands on their time and attention and have reason to be skeptical of the professional development advice they receive from researchers and other experts. We designed an intervention that overcame these obstacles and successfully motivated high-school teachers to adopt specific practices that support students' growth mindsets. The intervention used the values-alignment approach. This approach motivates behavioral change by framing a desired behavior as aligned with a core value—one that is an important criterion for status and admiration in the relevant social reference group. First, using qualitative interviews and a nationally representative survey of teachers, we identified a relevant core value: inspiring students' enthusiastic engagement with learning. Next, we designed a ~45-min, self-administered, online intervention that persuaded teachers to view growth mindset–supportive practices as a way to foster such student engagement and thus live up to that value. We randomly assigned 155 teachers (5,393 students) to receive the intervention and 164 teachers (6,167 students) to receive a control module. The growth mindset–supportive teaching intervention successfully promoted teachers' adoption of the suggested practices, overcoming major barriers to changing teachers' classroom practices that other scalable approaches have failed to surmount. The intervention also substantially improved student achievement in socioeconomically disadvantaged classes, reducing inequality in educational outcomes.

socioeconomic inequality | behavioral science | field experiment | growth mindset | values alignment

Significance

Large socioeconomic inequalities have long persisted in the US education system. We tested a method to reduce this inequality by motivating high-school teachers to adopt classroom practices that demonstrate a belief in students' capacity to learn and improve. The intervention successfully encouraged teachers to adopt these practices and thereby improved academic achievement in classes with higher proportions of students facing socioeconomic disadvantages. This study provides evidence for a method to help address socioeconomic inequality in educational outcomes by targeting teachers with scalable interventions. This method is a promising alternative to existing approaches that place the burden of change primarily on disadvantaged students themselves, rather than seeking to create more equitable learning environments.

The United States is currently one of the most socioeconomically unequal developed countries in the world (1) and has one of the lowest rates of social mobility (2). For individuals who begin life on the lower end of the socioeconomic spectrum, education offers the most obvious and promising vehicle for social mobility. It promises a path to higher-paying careers and the wide array of positive health and social benefits that are associated with a rise in socioeconomic status (SES) (3, 4). Unfortunately, young people from lower-SES backgrounds often encounter deeply entrenched structural barriers to their academic success. As a result, the American education system often reinforces and exacerbates existing socioeconomic inequality rather than reducing it (3, 5).

One aspect of the education system that can impact inequality in academic outcomes is the classroom culture: teachers' and students' shared system of goals, beliefs, and norms that define what it means to be a learner in that classroom (6–8, see refs. 9–11). Specifically, group-based disparities are exacerbated in classroom cultures characterized by the belief that intellectual abilities are fixed and cannot be meaningfully changed (i.e., a *fixed mindset classroom culture*) (8). Such classroom environments may be especially threatening for students who struggle or whose demographic group (e.g., race/ethnicity, socioeconomic background) is subject to negative stereotypes about academic potential. In such a classroom, these students may worry that these characteristics will be used to identify them as having immutably low levels of academic ability (12). Compounding this issue, evidence from a major international survey indicates that a high proportion (43%) of teachers endorse the stereotype that students from socioeconomically disadvantaged backgrounds are less capable of learning and improving academically than more advantaged students (12). This suggests that teachers may be especially likely to foster fixed mindset cultures in classrooms that primarily serve the very students who are most susceptible to that culture's negative effects, contributing to a cycle of inequality.

Because teachers are the primary authority figures in the classroom, their practices (i.e., what they say and do) have a powerful effect on the classroom culture (13–16, see refs. 9 and 17). Therefore, the most straightforward way for a teacher to remedy a fixed

Author contributions: C.A.H., C.J.B., and D.S.Y. designed research; C.A.H., C.J.B., and D.S.Y. performed research; C.A.H., C.J.B., and D.S.Y. contributed new reagents/analytic tools; C.A.H. and D.S.Y. analyzed data; and C.A.H., C.J.B., and D.S.Y. wrote the paper.

Competing interest statement: D.S.Y. and C.J.B. have disseminated growth mindset research to public audiences via paid speaking engagements or consulting, and they have complied with institutional financial interest disclosure requirements; currently no financial conflicts of interest have been identified.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: cameron.hecht@utexas.edu or christopher.bryan@mccombs.utexas.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2210704120/-/DCSupplemental.

Published June 12, 2023.

mindset classroom culture may be for them to adopt practices that intentionally foster a *growth* mindset classroom culture: One characterized by the idea that students' intellectual abilities are malleable and can be meaningfully improved (9). Indeed, when teachers endorse growth mindset *beliefs*—a common proxy for the growth mindset culture–building *practices*—group-based inequalities in academic outcomes have been found to be roughly half as large as when teachers endorse fixed-mindset beliefs (8).

In the present research, we developed an intervention aimed at motivating teachers to use specific communication practices that would help to foster a growth mindset classroom culture. These were practices that have been found, in past research, to be perceived by students as clear indicators of a teacher's support for the growth mindset (14–16, 18, 19, see ref. 9). We primarily targeted teachers' practices instead of their mindset beliefs because the latter cannot be directly observed by students, but the former are a direct and important driver of classroom culture (see ref. 9). We did anticipate, however, that one positive side effect of changing teachers' practices might be that they would shift their mindset beliefs to be consistent with the relevant practices (see refs. 20 and 21).

The teaching practices we sought to motivate, each consistent with basic tenets of growth mindset theory (see ref. 22), included a) conveying a belief in all students' capacity to learn and improve in the course (e.g., refs. 14, 15, and 18), b) putting less emphasis on students' current levels of performance and more emphasis on improvement over time (e.g., refs. 14, 15, and 19), c) taking every opportunity to make clear to students that what the teacher really cares about is that students put in the effort to push the limits of their learning (e.g., refs. 14 and 15), and d) providing assurance that if students put in that effort, they (i.e., the teacher) would provide the necessary support to ensure that that effort paid off (e.g., refs. 14–16). The intervention urged teachers to make these ideas a regular and central part of their classroom communication so that even skeptical students would eventually be persuaded that these beliefs were sincere and central to the teacher's philosophy of instruction. For the reasons articulated above, these changes in teachers' classroom communication were expected to improve academic achievement disproportionately in classrooms that serve students from lower-SES backgrounds.

Although effective interventions exist to teach students a growth mindset belief (see ref. 23), effective interventions that motivate teachers to adopt practices that support this mindset in their students do not yet exist (see ref. 10). Developing a scalable intervention that is effective for this purpose is challenging because there are many impediments to influencing teachers' classroom practices at scale (10). Teaching is a complex and demanding job—perhaps especially teaching adolescents, which is the focus of the present research. In addition to explaining content and monitoring learners' understanding of that content, teachers must provide emotional support, maintain discipline, serve as the primary point of contact for parents, and keep up with a large number of administrative and bureaucratic duties. Teachers often spend their initial years on the job figuring out how to balance these various, often-competing priorities (24, 25). So, unsolicited suggestions from administrators or outside experts that might upset this balance can feel impractical, overwhelming, or overly controlling (10, 25). This is likely why conventional professional development (PD) workshops have by-and-large failed to make meaningful changes in teaching practices (26, 27). Thus, for any teacher-focused intervention to be successful, it must first persuade teachers that they should devote their scarce time and effort to implementing an externally suggested change to their teaching.

Changing Teacher Behavior with Values Alignment. To accomplish this goal, we developed a brief, scalable growth mindset–supportive teaching intervention using the *values-alignment* framework (28–30). Values alignment is an approach designed to create strong internalized motivation for individual-level behavioral change. It works by reframing the desired behavior in terms of how it serves one or more core values that a person shares with an important social reference group (e.g., a professional community) and, when necessary, dispelling any perceived misalignment between the behavior and other personally important values (28). Such reframing imbues the relevant behavior with a sense of motivational priority by linking it with people's strong drive to live up to the (often tacit) standards they share with their peers and other members of their important social reference groups about what constitutes a person worthy of respect and admiration in their social milieu (28–30). As a result, the values-alignment approach can be effective at changing behaviors that are typically thought to be beyond the reach of conventional intervention approaches (28–30).

For example, a previous intervention that targeted adolescents using the values-alignment approach reframed healthy dietary choices as a way to enact the core adolescent values of autonomy from adult control and the pursuit of social justice. By framing healthy eating as a way to stand up against food companies that use deceptive marketing to manipulate people into eating unhealthy food, the intervention allowed adolescents to see healthy eating as a way to be the kind of rebellious and socially conscious adolescent that their peers would respect and admire. In two randomized controlled trials (29, 30), this brief intervention caused substantial and lasting improvements in adolescents' dietary choices. Thus, values alignment was effective at changing behavior in a domain (adolescent antiobesity interventions) that was otherwise characterized by null or iatrogenic effects (31).

The fundamental principle behind values alignment is that it is generally much easier to link a desired change in behavior with people's *existing* priorities (e.g., earning the respect or admiration of their peers by living up to shared values) than it is to persuade people that they should *change* their priorities (e.g., care more about being healthy in the future). This is why values alignment might succeed at influencing teachers' classroom practices where a more conventional approach might fail. A values-aligned intervention to encourage the adoption of growth mindset–supportive teaching practices would reframe the rationale for such practices in terms that make clear how they serve one or more of teachers' existing top priorities.

The Present Research. We developed the growth mindset–supportive teaching intervention for teachers in an academic environment in which recent policy changes aimed at reducing inequality have so far not led to the hoped-for improvements. Specifically, policy efforts to broaden access to rigorous high-school courses have increased in recent years (32, 33). Dual-enrollment programs that allow high-school students to take college-level courses and earn both high school and college credit concurrently (34) have become more prevalent over the past decade (35, 36). Although this is a worthwhile effort, evaluations have found that most students from low-SES backgrounds fail these courses (37), further reinforcing fixed-mindset stereotypes about the college worthiness of those students. We reasoned that, if our intervention motivated teachers to adopt practices that support a growth mindset classroom culture, this would help reduce socioeconomic disparities in success rates in these dual-enrollment courses, opening the door to social mobility.

The research reported here comprised two distinct phases: a design phase (Fig. 1) and an evaluation phase (Fig. 3). During the

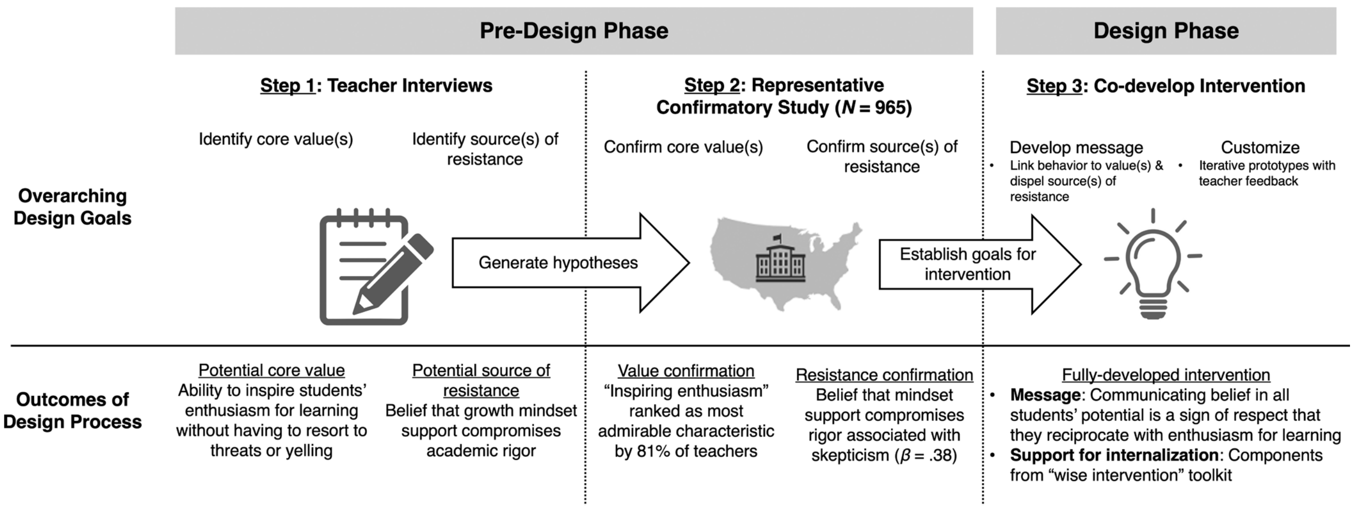

Fig. 1. Design process for developing the growth mindset–supportive teaching intervention. In Step 1, we interviewed a convenience sample of dual-enrollment teachers. The goals of the interview were to identify (a) at least one core value among teachers (i.e., a characteristic that they see as indicative of a teacher's worthiness of respect and admiration from their colleagues) and (b) any potential sources of resistance to adopting growth mindset–supportive practices (i.e., perceived misalignments between these practices and another important value). In Step 2, we confirmed one potential core value (i.e., the ability to inspire students' uncoerced enthusiasm for learning) and one potential source of resistance to growth mindset–supportive practices (i.e., the belief that these practices involve compromising rigorous academic standards) in a nationally representative sample of math teachers. In Step 3, we developed the values-aligned intervention argument by framing the targeted practices as a means to inspire student enthusiasm for learning while dispelling the notion that these practices involved sacrificing academic rigor. We crafted the intervention in iterative design cycles with feedback from dual-enrollment teachers.

design phase, we used focus group interviews and a confirmatory, nationally representative survey study to identify a) a core shared value that could be harnessed in an intervention using the values-alignment approach, and b) perceived misalignments between growth mindset–supportive practices and other important values or goals that might lead teachers to resist behavioral change (Fig. 1). We then used the findings from these interviews and surveys to develop a ~45-min interactive online intervention training module that framed the adoption of growth mindset–supportive teaching practices as a way to live up to the identified core value (described next). During the evaluation phase (Fig. 3), we tested the growth mindset–supportive teaching intervention among high-school teachers and their students in dual-enrollment courses. To assess inequality-reducing effects, we focused on performance benefits in classrooms with higher concentrations of students from low-SES families.

Design Phase

Using interviews with convenience samples of instructors teaching dual-enrollment courses (Fig. 1, Step 1), we found evidence that one value, in particular, was a key criterion for admiration and prestige among teachers: *being able to inspire students' enthusiasm for learning instead of resorting to coercion (e.g., threats, yelling)*. Teachers reported feeling especially disheartened when their students were disengaged and seemingly could not be motivated to pay attention unless the teacher took a domineering approach. Teachers were therefore in wide agreement that the most admired teachers were those few for whom, upon walking into the classroom, students would immediately perk up and pay attention without any need for coercion.

To validate these preliminary findings, we conducted a survey study in a separate, nationally representative sample of math teachers in the United States (N = 965) (preregistration: https://osf.io/23e57/). In this confirmatory study (Fig. 1, Step 2), teachers ranked the importance of seven characteristics in "helping a teacher to earn the professional respect of their colleagues."

The list of characteristics included, for example, holding an advanced degree, consistently achieving high student standardized test scores, and being exceptionally well organized. Our primary interest was the relative ranking of the following characteristic, which stood out as most important in our qualitative interviews: *"They inspire enthusiasm for learning in all of their students—even those who are withdrawn or disruptive in other classes—without the need for threats or yelling".* Consistent with our hypothesis, 81% of teachers ranked inspiring student enthusiasm for learning as the single most important of the seven characteristics—far more than any of the others (Fig. 2). Interrogating the heterogeneity in this national sample, we found that inspiring student enthusiasm for learning was rated as the most important characteristic for each teacher gender, race, and education-level subgroup and each

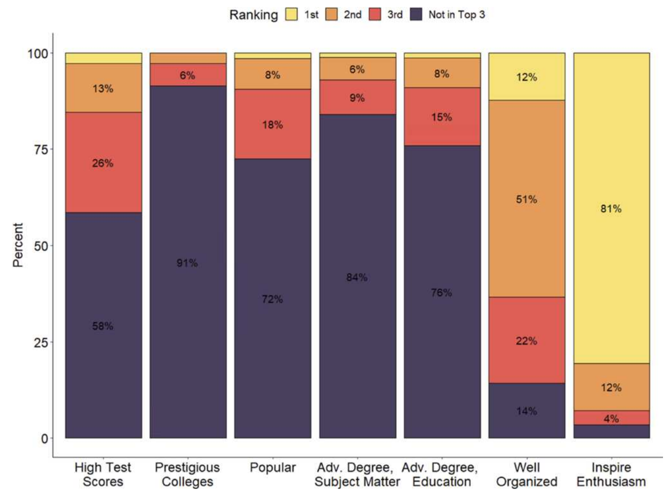

Fig. 2. Teacher rankings of the importance of each of seven possible characteristics for helping a teacher to earn the professional respect of their colleagues. See *SI Appendix*, *Text* for the exact wording of all characteristics. Inspiring student enthusiasm for learning was ranked in the top 3 by 97% of teachers, and as the single most important characteristic by 81% of teachers. Text not included for percentages <4%. A random intercept multilevel linear model (i.e., repeated rankings of the seven characteristics nested within each teacher) showed that teachers consistently ranked inspiring student enthusiasm for learning higher than any of the other six characteristics (P < 0.001, d > 1.36, for each pair-wise comparison).

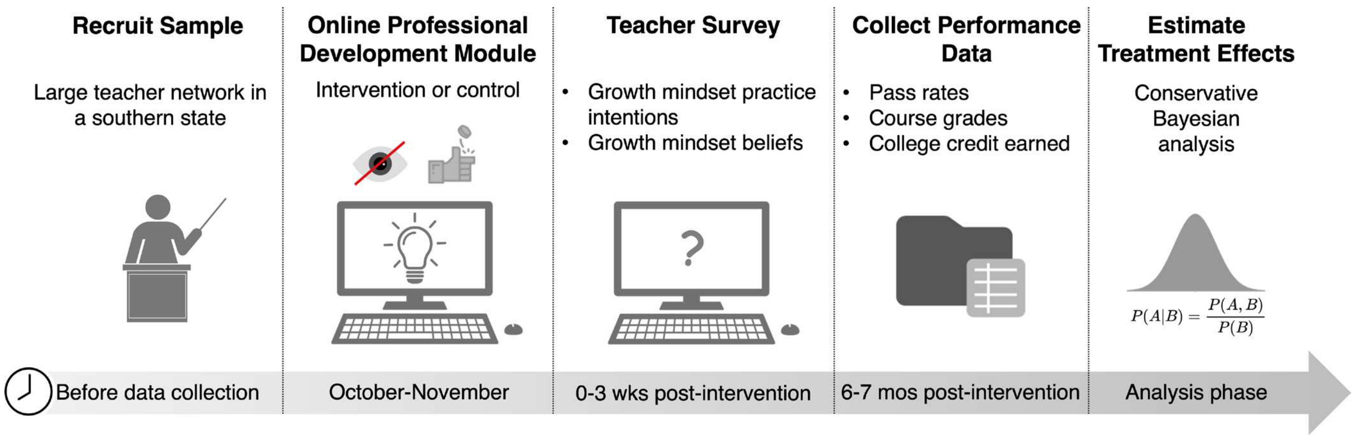

Fig. 3. Process for evaluating the growth mindset–supportive teaching intervention. Teachers were randomly assigned to complete an intervention or control module between October 26 and November 15 of 2020. They then reported their growth mindset beliefs and growth mindset practice intentions 0 to 3 wk postintervention. Student performance data were collected at the end of the school year (6 to 7 mo postintervention). We used a conservative Bayesian analysis to assess treatment effects.

school size, urbanicity, SES, and racial composition subgroup (>75% for each subgroup).

Our interviews also identified a potential source of misalignment between growth mindset–supportive practices and teachers' other priorities. In particular, a number of teachers mentioned the concern that support for students' growth mindsets might require teachers to compromise their standards for academic rigor. This perception seemed to stem from the mistaken belief that growth mindset practices involve simply comforting struggling students without holding them accountable for their learning. We hypothesized that teachers with this misperception would tend to be more skeptical of growth mindset–supportive teaching practices.

A second preregistered analysis with our national survey data confirmed this hypothesis. We measured teachers' perceptions that supporting students' growth mindsets would require them to compromise academic rigor (i.e., "How much do you believe that when teachers regularly and strongly emphasize their support for students' growth mindsets, it causes teachers to lower their standards of academic rigor or hard work?"). This misconception was meaningfully associated with skepticism about the prospect of supporting students' growth mindsets (i.e., "Are you generally more skeptical or more enthusiastic about the idea of regularly and strongly emphasizing your support for students' growth mindsets in your own teaching?"), $\beta = 0.38$, $P < 0.001$. These results held when controlling for teacher gender, race, and education level and school size, urbanicity, SES, and racial composition. Interestingly, the association was significantly stronger in low-SES schools, $\beta = 0.48$, $P < 0.001$, than in high-SES schools, $\beta = 0.28$, $P < 0.001$ ($P = 0.007$ for the Rigor × School SES interaction). This suggests that emphasizing the link between growth mindset–supportive practices and maintaining rigorous standards may be especially important for persuading teachers in low-SES contexts to adopt these practices.

The Growth Mindset–Supportive Teaching Intervention. Informed by this preliminary work (Steps 1 and 2 in Fig. 1), we designed an intervention that encouraged teachers to adopt growth mindset–supportive practices (Step 3 in Fig. 1). The intervention comprised two halves. In the first half, the intervention used a values-aligned argument that connected the targeted behavior—growth mindset–supportive teaching practices—to the core value identified in the prior interview and survey research: inspiring enthusiastic student engagement with the learning process. In the second half, the intervention provided guidance on exactly how teachers could use the recommended practices. See *SI Appendix*, *Text* for illustrative intervention excerpts.

The logic of the values-aligned argument (articulated in the first half of the intervention) was as follows:

1. Hormonal changes in adolescence make teenage students especially attuned (and even "hypersensitive") to cues of respect and disrespect from adults (38–40).
2. Subtle and even unintentional cues from teachers can cause students to conclude that their teacher does not believe in their potential to learn and improve.
3. Because the core purpose of the teacher–student relationship is for students to learn from teachers, students' perception that their teacher does not see them as capable of learning is likely to cause students to feel that their teacher sees them as unable to fulfill their role in the class and therefore as a poor investment of the teacher's time and energy.
4. This perception causes students to feel disrespected by their teachers.
5. When students feel disrespected in this way, they are likely to react by either disengaging or reciprocating the perceived disrespect (e.g., by acting out in class).
6. On the contrary, students' hypersensitivity to respect also presents teachers with an *opportunity*. If teachers provide students with clear cues of respect—specifically, that they believe in their students' potential to learn and improve—students tend to reciprocate this perceived respect with enthusiastic engagement.

In the second half of the intervention, the module provided examples of how teachers could provide clear cues of respect, focusing primarily on things teachers could say to communicate their belief in all students' potential to improve and master the material (see Table 1 for examples). As noted above, these examples were consistent with core tenets of growth mindset theory (see ref. 22) and grounded in previous research on messages that students interpret to be unambiguous indicators of a teacher's support for the growth mindset (see refs. 9 and 17). We included numerous examples of different ways to communicate the same core ideas. We did this for two primary reasons: 1) to increase the likelihood

Table 1. Excerpts from the growth mindset–supportive teaching intervention

Intervention excerpt
"I don't care about how much you know right now; I care about how much you've learned by the end of the year, and as long as you put in the work, I'll be here to help you make sure that work pays off."
"Where you start out isn't important to me. What matters to me is that each of you makes major progress... more than you probably think you can make."
"[...] tests are just indicators of what students know right now... I want to see that you're learning and becoming confident with the material. Tests help me to see where you're at and how I can help you to improve beyond that place."
"I'm not going to tolerate slacking, but I'm also not going to expect every student to know the best ways to [learn]—that's what I'm here for."
"There isn't a single person in this class that I don't expect to push the limits of their understanding and ability..."
"[...] struggle is the path to strength and improvement, and 'easy' is the path to stagnation and atrophy."

Each of the excerpts—included in the second half of the intervention—was part of a concrete example intended to demonstrate to teachers how they could effectively communicate a belief in every student's ability to learn and improve. These demonstrative examples were carefully crafted to include a combination of high standards for effort, assurance that students are capable of improvement, and that the teacher would provide support to any student who put in the effort to improve.

that at least some examples would resonate with every participating teacher as the kind of thing they could implement in their own classroom and 2) to help teachers gain as deep an understanding as possible of the full complexity of these ideas.

Importantly, the examples in the module emphasized teachers' high standards, illustrating that supporting students' belief in their potential to improve is fully consistent with maintaining high standards of academic rigor (e.g., "[…] struggle is the path to strength and improvement, and 'easy' is the path to stagnation and atrophy."). Highlighting how teachers could maintain high standards while expressing a sincere belief in their students' potential to learn and improve was intended to dispel potential perceptions of misalignment between growth mindset–supportive practices and being the kind of teacher who holds students to rigorous academic standards.

Throughout the intervention, we used tools that are typical of "wise interventions" to promote internalization of the intervention message (41, 42). For example, we gave teachers the opportunity to develop growth mindset–supportive messages, in their own words, that they would like to communicate to their students (43). We also asked them to make concrete plans about how and when they would communicate these messages (44).

Note that the values-aligned approach differs considerably from previous interventions aimed at fostering growth mindset–supportive teaching practices. Those previous interventions have typically focused on providing teachers with evidence of brain malleability as well as prewritten lessons and classroom activities to deliver to students (e.g., refs. 45 and 46). By contrast, the values-aligned intervention was designed to *motivate* teachers to prioritize growth mindset–supportive teaching practices, even if they were not already convinced that these practices should be a priority. The values-aligned intervention was also expressly designed to be scalable. It involves only a single brief, self-administered training session and does not require teachers to sacrifice class time to provide prescribed lessons.

Evaluation Phase

We tested the growth mindset–supportive teaching intervention in a teacher-level randomized controlled trial during the 2020-21 school year (when COVID-19 forced most teaching to be conducted virtually for at least part of the year) (https://osf.io/ncxtm). The study was conducted in dual-enrollment courses in high schools throughout a large southern state. Teachers were individually and randomly assigned to condition (intervention: $n_{teachers}$ = 155, $n_{students}$ = 5,393; control: $n_{teachers}$ = 164, $n_{students}$ = 6,167). A total of 7,650 of these students were enrolled in a science, technology, engineering, or mathematics (STEM) course (e.g., precalculus), and 3,910 students were enrolled in a non-STEM course (e.g., rhetoric).

The study procedure is summarized in Fig. 3. Prior to randomization, teachers reported their growth versus fixed mindset (agreement with items like "A student who starts the beginning of the year near the bottom of the class rarely ever has the potential to become a high performer," reversed). In late October/early November, teachers completed a brief training module (~45 min) corresponding to their experimental condition. Teachers in the control condition received a module focused on maximizing the accessibility of material while teaching virtually (e.g., using clearer fonts, visual aids, and frequent summaries to accommodate students' individual learning differences).

Teachers were asked to respond to a follow-up survey sometime within the three-week period immediately following the intervention. The survey assessed whether teachers intended to enact growth mindset–supportive practices consistent with the recommendations in the growth mindset–supportive teaching intervention (e.g., "Say or do something in your class that communicates you believe in every student's potential to learn and improve"). We also measured teachers' postintervention growth mindset beliefs. Although changing teachers' growth mindset beliefs was not our primary objective, we reasoned that if we increased teachers' motivation to adopt growth mindset–supportive teaching practices, they would be likely to update their mindset beliefs to be consistent with those intended practices (20, 21). At the end of the school year (6 to 7 mo postintervention), we collected data on students' pass rates and grades in the course from official school transcripts.

Analysis Using Bayesian Causal Forest (BCF). We tested the effects of the intervention using BCF analysis, which is a conservative machine-learning algorithm (47). Like frequentist methods, BCF estimates both average treatment effects (ATEs; commonly referred to as main effects) and moderation of treatment effects. However, unlike frequentist approaches, BCF produces these estimates by first estimating a posterior distribution, which is a function of the observed data and a prior distribution that represents a priori expectations about the existence and strength of any systematic effects. BCF uses a highly conservative prior distribution—one that is designed to shrink estimates of average and moderation effects toward zero. As such, both average and moderation effect estimates from BCF tend to be substantially smaller (i.e., more conservative) than those generated by frequentist models, which do not incorporate a conservative prior (see, for example, the estimates in Table 3).

When estimating ATEs (i.e., main effects), the primary difference between an estimate produced by BCF and one produced by a frequentist model is that the former tends to be more conservative. In the present research, the relevant "main effect" tests are of the intervention's effect on teachers' intentions to implement the recommended growth mindset–supportive teaching practices and on their mindset beliefs.

The major advantage of BCF, however, is its ability to test moderators of treatment effects while effectively guarding against the risk of false-positive conclusions. Indeed, in head-to-head comparisons with other competing methods, BCF has been found to be the most effective existing modeling strategy for identifying true, systematic moderators of treatment effects (48). In the present research, the relevant test is of whether classroom SES systematically moderates the intervention's effects on student academic achievement.*

Below, we summarize the posterior distribution of treatment effects by presenting the average of that distribution (i.e., the estimate of the ATE) and the average of the distribution within subgroups (i.e., the conditional average treatment effects [CATEs]). To test for moderation (i.e., interaction effects), we subtract the posterior distribution of the treatment effect in one subgroup from another to form a posterior distribution of the difference, which informs whether treatment effects differ between subgroups (i.e., are moderated). To characterize the variability within the posterior distribution, we also report the interval of that distribution between the 10th and 90th percentiles. To characterize the level of certainty that a systematic effect is different from zero, we report the proportion of the posterior distribution that is greater than zero (which can be interpreted simply as the estimated probability that the effect is greater than zero; reported as "pr()"). Following our registered standards (https://osf.io/ncxtm), we do not interpret an effect with <0.75 posterior probability to be meaningful, and we interpret posterior probabilities >0.75 continuously, with higher probabilities indicating greater confidence in the effect. We also report complete results from conventional frequentist models in *SI Appendix*, Table S13, and the results from those models support substantively identical conclusions to those reported here in the main text.

It is important to note that our emphasis on reporting Bayesian posterior probabilities, in lieu of *P* values, to quantify the certainty associated with effect estimates is consistent with calls to abandon the all-or-nothing thinking inherent in statistical significance testing and instead report probabilities that a hypothesis is true as a continuous measure (49, 50, see refs. 51–53 for other examples of published research that employs this approach to hypothesis testing). Further, because we use Bayesian posterior probabilities, we avoid problems with the misinterpretation of *P*-values in classical hypothesis tests (54). Finally, BCF's reliance on a machine-learning algorithm dramatically reduces the need for researchers to make analytical decisions (e.g., about which potential moderators and covariates should be included in the model) and therefore reduces researcher degrees of freedom that often inflate the risk of Type I error (55).

Expected Effect Sizes. It is important to consider what effect sizes on students' academic achievement (i.e., grades, course pass rates) would be meaningful in the present intervention trial. Throughout the paper, we will refer to effect sizes in terms of standardized mean differences (*SMD*)—that is, differences in SD units. This statistic is conceptually equivalent to Cohen's *d*, but, unlike *d*, can be calculated from model estimates as well as from raw data. A fifth of a SD (i.e., *SMD* = 0.20) is considered a large effect in real-world educational settings (56). An effect of this magnitude corresponds roughly to a) the amount of improvement students show on standardized test scores after a year of classroom learning in high school (57), b) the effect of having a high-quality teacher (versus an average teacher) for 1 y (58), and c) the most optimistic estimates of the effects of costly interventions that are difficult to scale, such as individualized tutoring (59). Given how inexpensive and easy the present module would be to scale, it would be noteworthy if the growth mindset–supportive teaching intervention achieved any meaningful proportion of this effect size.

When comparing the effects reported below to these benchmarks, it is important to note that a feature of BCF is that it shrinks estimated treatment effects (and differences between treatment effects across levels of a moderator) toward zero. In fact, in the results reported here, effect sizes were shrunken by as much as ~50% relative to conventional estimates from linear models. We report effects both from BCF models and linear models to provide both conservative Bayesian estimates and conventional frequentist estimates. We also present descriptive statistics (i.e., raw means by condition for teacher outcomes, means by condition, and classroom SES composition for student performance outcomes) in Table 2.

Effects on Teachers' Intended Practices and Mindset Beliefs. We first tested effects of the intervention on a) teachers' intentions to use growth mindset–supportive practices in their teaching and b) teachers' growth mindset beliefs about students. The BCF analysis revealed that the intervention increased teachers' intentions to use growth mindset–supportive practices in their teaching by 0.19 *SD* [0.04, 0.33], pr(ATE > 0) = 0.96, relative to control. Consistent with our expectation that teachers might update their mindset beliefs to be consistent with their intended use of growth mindset–supportive teaching practices, the intervention also increased teachers' growth mindset beliefs by 0.22 *SD* [0.07, 0.37], pr(ATE > 0) = 0.98, relative to the control module. Using an ordinary least squares multiple regression model, these effect size estimates were 0.26 *SD* and 0.37 *SD* for intended practices and mindset beliefs, respectively.

Effects on Student Academic Achievement. Next, we tested whether the growth mindset–supportive teaching intervention had a reliable effect on students' academic achievement (i.e., pass rates, course grades, and earning college credit), which represented our primary test of behavioral change. As we noted earlier, dual-enrollment courses, which give students early exposure to college-level content, have high failure rates, especially among students from low-SES backgrounds (37). Increasing the rate at which students successfully complete these courses—particularly in lower-SES classrooms—could therefore help deliver on the college-preparatory promise of dual-enrollment courses. Course grades, on the contrary, hold less immediate policy relevance but provide a related continuous outcome to test intervention effects. Finally, earning college credit is not only of policy relevance, allowing students to contribute to their college transcript before beginning college, but it is also useful for research purposes because it was determined by students' performance on assessments that were graded by college professors who were unaware of the intervention and therefore could not have been directly influenced by the grading practices of the high-school teachers who received the intervention.

We tested whether the effects of the growth mindset–supportive teaching intervention on these three achievement outcomes were systematically moderated by the SES composition of the class (i.e., the proportion of students from low-SES backgrounds). Previous research, referenced above, indicates that many teachers hold fixed mindset beliefs specifically about the academic potential of lower-SES students because they doubt whether anything teachers can do will be sufficient to overcome the substantial barriers these

*For a more complete and technically detailed description of how BCF and related Bayesian Additive Regression Tree approaches work, see refs. 47 and 63.

Table 2. Raw means and SDs by condition for the teacher-intervention RCT

Outcome	SES classroom composition	Control			Growth mindset–supportive teaching intervention		
		M	*SD*	*N*	*M*	*SD*	*N*
Postintervention practice intentions	—	0.35	0.39	122	0.45	0.40	109
Postintervention mindset beliefs	—	0.52	0.45	122	0.63	0.40	109
Average pass rates (standardized)	Majority low-SES	−0.49	1.01	92	−0.24	1.01	77
	Majority high-SES	0.47	0.76	72	0.38	0.82	78
Average course grades (standardized)	Majority low-SES	−0.49	0.86	92	−0.22	1.00	77
	Majority high-SES	0.45	0.89	72	0.38	0.93	78
Average college credit earned (standardized)	Majority low-SES	−0.48	0.98	92	−0.30	0.96	77
	Majority high-SES	0.49	0.82	72	0.42	0.84	78

Student performance variables are standardized, at the request of our partnering PD network, to protect the confidentiality of these sensitive data.

students face (12). Therefore, in classrooms where a majority of students are from low-SES backgrounds, teachers may be less likely to already be communicating (explicitly or implicitly) a belief in every student's potential to learn and improve. They might also be more likely to be communicating the opposite belief (i.e., a fixed mindset), either intentionally or unintentionally. Thus, we reasoned that students in majority-low-SES classrooms would be especially likely to benefit from an increase in their teachers' express support for the growth mindset.

The BCF model revealed that, on average, the intervention increased pass rates by 3.59 percentage points [1.14, 6.04], pr(ATE > 0) = 0.97, *SMD* = 0.07, and course grades by 0.10 grade points [0.01, 0.18], pr(ATE > 0) = 0.94, *SMD* = 0.07. These overall effects, which were caused by a single 45-min intervention, are equivalent to approximately 35% of the average effect of an entire year of classroom learning in high-school math (*SMD* = 0.20), and therefore demonstrate the potential for a meaningful, scalable impact. In addition, as noted above, BCF produces shrunken estimates of effect sizes to ensure that it generates a conservative estimate of the probability than an effect is systematically different from zero. Estimates using a conventional multilevel linear model were 5.27 percentage points (*SMD* = 0.11) and 0.18 grade points (*SMD* = 0.12) for pass rates and course grades, respectively.

Did the intervention reduce inequality? It did. The model also found that treatment effects were stronger in classrooms with a higher percentage of low-SES students. The estimated probability of a positive difference in treatment effects between majority low-SES classrooms (i.e., >50% low-SES students) and majority high-SES classrooms (≤50% low-SES students) was 0.97 and 0.86 for pass rates and grades, respectively.

In majority low-SES classrooms, BCF estimated that the intervention increased pass rates by 6.31 percentage points [2.67, 9.83], pr(CATE > 0) = 0.99, *SMD* = 0.13, and course grades by 0.14 grade points [0.02, 0.25], pr(CATE > 0) = 0.96, *SMD* = 0.10. By contrast, in classrooms with a low percentage of low-SES students, the intervention increased pass rates by 1.18 percentage points [−1.66, 3.95], pr(CATE > 0) = 0.71, *SMD* = 0.02, and course grades by 0.06 grade points [−0.01, 0.15], pr(CATE > 0) = 0.83, *SMD* = 0.04 (Fig. 4). Using conventional frequentist estimates (derived from a multilevel linear model), the effect sizes in majority low-SES classrooms were 10.65 percentage points (*SMD* = 0.22) and 0.36 grade points (*SMD* = 0.25) for pass rates and course grades, respectively (Table 3). Thus, the conservative Bayesian estimates were at least 50% of the threshold for a "large" effect in a real-world setting noted above (0.20 *SD*) (56), and the conventional frequentist estimates actually exceeded this threshold. Both estimates suggest that the growth mindset–supportive teaching intervention holds great promise as a scalable approach to improve students' academic outcomes, particularly in lower-SES settings where promoting achievement may be especially impactful for students' future socioeconomic prospects.

Did the intervention simply cause teachers in low-SES classrooms to grade more leniently? On its face, this explanation seems less than plausible. There is no obvious reason why the growth mindset–supportive teaching intervention would cause teachers to grade more leniently, given its emphasis on pushing students to stretch the limits of their understanding and ability. There is even less reason to believe that the intervention would have had this effect specifically on teachers in majority low-SES classrooms.

Table 3. Estimated treatment effects on pass rates, course grades, and college credit earned as a function of classroom percentage of low-SES students from BCF and multilevel linear models

		Multilevel BCF			Multilevel linear model		
Outcome	SES classroom composition	CATE	pr(CATE > 0)	Probability of difference between CATEs	CATE	T statistic (CATE)	T statistic (interaction)
Pass rate	Majority low-SES	6.31 PP	0.99	0.97	10.65 PP	3.21	2.39
	Majority high-SES	1.18 PP	0.71		−0.10 PP	−0.03	
Course grade	Majority low-SES	0.14 GP	0.96	0.86	0.36 GP	3.27	2.44
	Majority high-SES	0.06 GP	0.83		−0.00 GP	−0.04	
College credit earned	Majority low-SES	3.71 PP	0.95	0.91	7.35 PP	2.43	1.54
	Majority high-SES	1.07 PP	0.73		0.10 PP	0.33	

Note: PP = percentage points, GP = grade points, pr(CATE > 0) = proportion of draws from the posterior distribution for the CATE that were greater than zero. College credit earned (the third performance outcome) was determined by students' performance on college assessments that were graded by college professors. (Note: 1% of students also failed to earn college credit despite earning a passing college grade because they did not pass the high school course and were therefore ineligible. The average college grade among these students was a D). Pass rates and course grades were determined by students' high school teachers. BCF estimates summarize the posterior distribution for classes with a majority (>50%) of low-SES students or a majority (≥50%) of high-SES students. Multilevel linear model results provide simple effects for classes with a majority of low-SES or a majority of high-SES students.

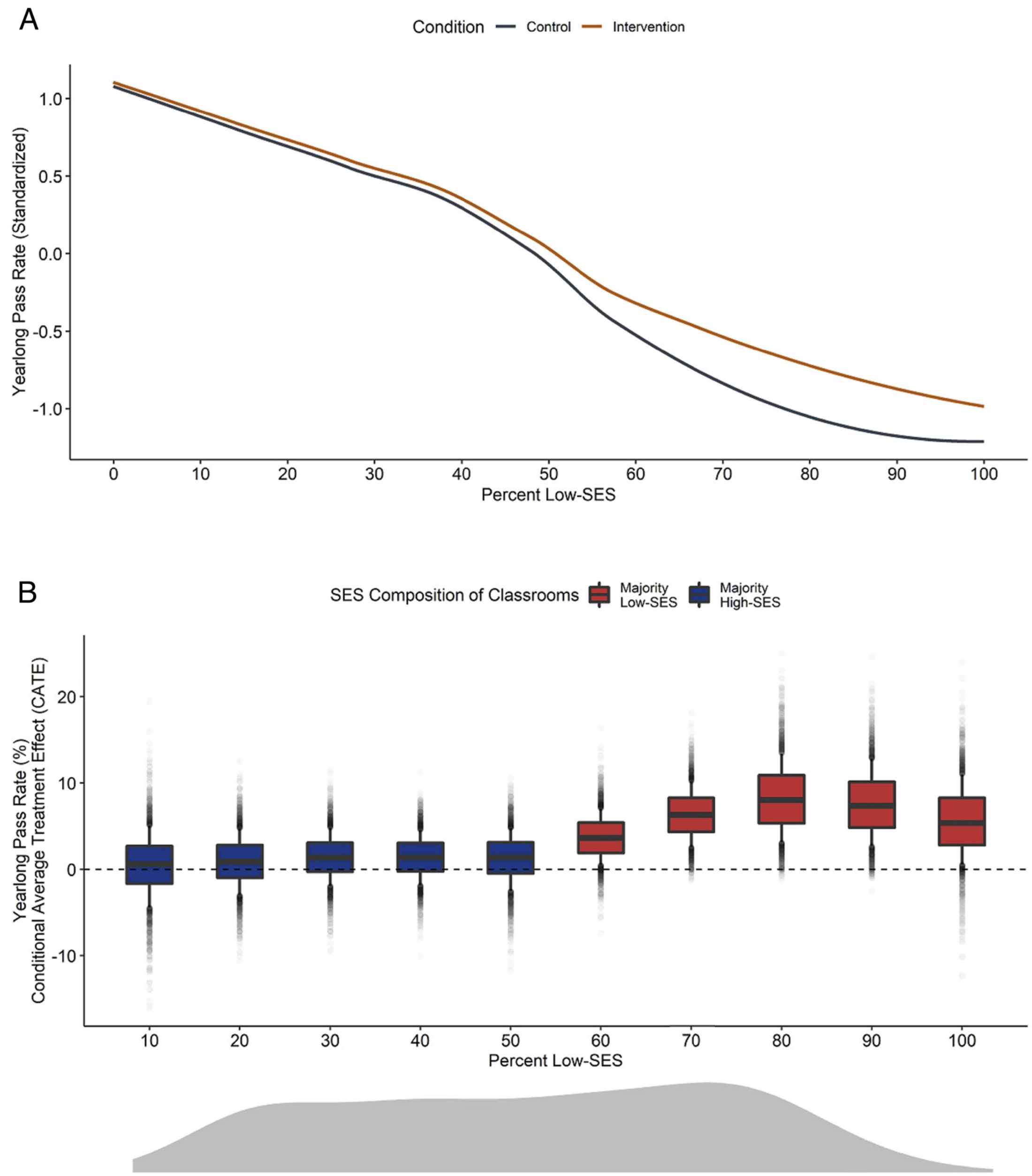

Fig. 4. Effects of the growth mindset–supportive teaching intervention on course performance. Panel *A* displays the predicted values of yearlong pass rate (standardized) as a function of condition and SES classroom composition (using LOESS smoothing) estimated in a Bayesian causal forest (BCF) analysis. Note the strong tendency for overall pass rates to decline as the percentage of low-SES students in a class increases. Panel *B* displays the conditional average treatment effect (CATE) as a function of the SES classroom composition, estimated in the BCF analysis. Boxes represent the interquartile range of the posterior distribution at each 10% interval of SES classroom composition, whiskers represent the range from the 10th to 90th percentile of the distribution, and points represent draws from the posterior distribution that fall outside this range. The distribution of the percentage of low-SES students in classrooms is displayed beneath the two panels. Yearlong pass rate is graphed to illustrate the treatment effects, but patterns are similar for the other student outcomes (see *SI Appendix*, Fig. S1 for graphs of the other outcomes).

For example, the intervention never mentions student SES or any other vulnerable group that overlaps with low SES.

In addition, as noted above, the structure of these dual-enrollment courses provided a unique opportunity to rule out this possibility empirically because college credit is determined by assessments that are graded by college professors who had no exposure to any intervention content, nor any contact with the high-school teachers postintervention. We found that the intervention increased rates of earning college credit overall by an average of 2.31 percentage points [0.01, 4.73], pr(ATE > 0) = 0.90, *SMD* = 0.05, and by 3.71 percentage points [0.53, 6.87], pr(ATE > 0) = 0.95, *SMD* = 0.08, in majority low-SES classrooms. Using a conventional multilevel linear model, these estimates were 4.19 percentage points (*SMD* = 0.09) overall, and 7.35 percentage points (*SMD* = 0.15) in majority low-SES classrooms (Table 3). Thus, these results represent true effects on student learning that were caused by the values-aligned intervention module.

Discussion

Even using BCF's conservative estimates, the practical significance of these effects is striking. For example, a conservative estimation (see *SI Appendix*, *Text* for details) suggests that, if the growth mindset–supportive teaching intervention were delivered to every teacher in the United States, the 6.31 percentage point effect on pass rates (the estimated CATE from BCF in majority low-SES classes) would translate to roughly 157,750 more students in high-poverty US schools, who pass their dual-enrollment courses each year, for the cost of one 45-min, self-administered online teacher training.

In addition, the present findings suggest that helping teachers find better ways to support and motivate students can be even more effective than intervening directly with students. According to the best estimate currently available (52), an intervention that teaches growth mindset directly to students improves academic performance by 0.10 grade points ($SMD = 0.11$) among at-risk students (i.e., those with low prior achievement). By contrast, the current teacher-targeted intervention improved performance for the at-risk group (i.e., students in low-SES classes) by 0.36 grade points ($SMD = 0.25$), as estimated by a similar multilevel linear model—a more than twofold increase in effectiveness. Although the samples on which these two estimates are based are not perfectly comparable, this apparent increase in effect size is consistent with the mindset + supportive context hypothesis that growth mindset effects on student outcomes are larger when teachers are supportive of those student mindsets (17, 51).

The design of this study and the present analyses have several strengths that fortify the conclusions presented here. In particular, the study used a randomized controlled design—the "gold standard" for intervention evaluations—with a sample of more than 150 teachers and 5,000 students per condition, which is large compared to other studies evaluating interventions with teachers (e.g., see ref. 60). In addition, we followed a disciplined preanalysis plan to evaluate effects on teachers' mindset beliefs and intentions to enact growth mindset–supportive practices, as well as conservative Bayesian models to test effects on these outcomes and on student performance outcomes. These strengths suggest that the results presented here are unlikely to be attributable to Type-I error and that the practical implications of these findings should be taken seriously.

This research also raises many interesting questions for future research. For instance, how important is it that all teachers—in treatment and control—also received training in pedagogical best practices for their disciplines? Although the lasting effects of this brief, single-session intervention are striking, might those effects be even greater if the intervention were complemented by ongoing training and support? If so, would it be possible to make that follow-on training as scalable and efficient as the intervention module, for example, through virtual professional learning communities (in which teachers share ideas and insights with one another as they refine their growth mindset–supportive practices)?

A notable aspect of our intervention philosophy is that it is asset based. Many conventional approaches to teachers' PD have tended focus on addressing deficits teachers are presumed to have, such as a lack of sufficient motivation or instructional skill. The values-alignment approach, on the contrary, did not assume that teachers had these deficits, but instead, assumed that most teachers are deeply motivated to be the kind of person who helps struggling students succeed (25, 61). The present research demonstrates the power of tapping into teachers' aspirations to be the best versions of themselves. Using this approach, behavioral change is possible even in areas where previous approaches have failed.

Finally, this study demonstrates the potential of an alternative approach to bringing about systemic change. Changing a system is often understood to mean *policy* changes. Though essential, changing the policies in a system—which can be challenging and time-consuming—may not be the only option. Instead, the growth mindset–supportive teaching intervention sought to change teachers: the "frontline" members in the education system who are responsible for carrying out the goals of the system and have significant discretion about how they do so. The present research provides an important demonstration that an intervention targeting the frontline members in a system can help to ameliorate the system's inequality-reinforcing effects. We believe this approach also holds promise for countering the inequality-reinforcing effects of other unfair systems; for instance, interventions could target frontline individuals in the workplace (e.g., managers), health care (e.g., doctors, nurses), and criminal justice (e.g., police, parole officers) to improve outcomes for the individuals who are directly affected by the system. In each case, an effective values-aligned intervention would begin by identifying values that are common among the frontline members of these systems that could be harnessed to motivate changes in their behavior. Our hope is that values alignment proves to be a powerful tool to counter the inequality-reinforcing effects of society's important institutions, even when changes to policy remain stubbornly out of reach.

Materials and Methods

Correlational Survey Study. This study was approved by the University of Texas at Austin's Institutional Review Board under protocol 00001380. All participating teachers provided consent to participate. The design of this study was informed by qualitative interviews conducted by the research team. The data for this study came from a nationally representative sample of math teachers in the United States. Data were collected by the RAND Corporation from November to December 2021. The initial dataset consisted of 980 teachers. However, 15 of these teachers did not respond to any of the items used for the present analyses and were excluded, leaving a final analytic sample of 965 teachers.

Among the final sample, 49% taught high school, 40% taught middle school, and 11% taught elementary school. Seventy percent of teachers were female, 12% were Black or Hispanic/Latinx, and 63% held a Master's degree or higher. Seventy-eight percent of teachers taught in a school with at least 450 students, 24% in an urban school, 47% in a low-SES school (i.e., where the majority of students received free or reduced-price lunch), and 55% in a school where the majority of students were White. Teachers reported their perceptions of the importance of seven teacher characteristics for earning the professional respect of their colleagues, their beliefs that supporting students' growth mindsets involves compromising academic rigor, and their skepticism about supporting students' growth mindsets (see *SI Appendix*, *Text* for details).

Teacher Intervention Randomized Controlled Trial. This study was approved by the University of Texas at Austin's Institutional Review Board under protocol 2018080008. Participating teachers and students provided assent during registration. The data for this study came from high-school teachers within a PD network in a southern state and the students in their dual-enrollment courses. Historical data (from 2016 and 2017 in the same network) suggest that this population (students taking dual-enrollment courses in this network) was similar in racial/ethnic composition to the population of students in the same schools who were not enrolled in dual-enrollment courses. The population of dual-enrollment students, however, did have a somewhat lower proportion of students from low-income families. Dual-enrollment students were 9% Black and 47% Hispanic/Latinx; non-dual-enrollment students in the same schools were 13% Black, 49% Hispanic/Latinx. Thirty-eight percent of dual-enrollment students were from low-income families; 47% of non-dual-enrollment students in the same schools were from low-income families. The biggest difference between dual-enrollment and non-dual-enrollment students was that the former group had substantially higher standardized test scores (by approximately 0.5 SD).

In the present sample of schools, a median of 6% of students within a school were enrolled in a dual-enrollment course at the outset of the term. The percentage of students enrolled in a dual-enrollment course within a school was not significantly associated with campus proportions of students from low-SES families, students from underrepresented racial/ethnic groups (i.e., Black, Hispanic/Latinx, Native American, or Pacific Islander), or female students ($ps > 0.108$). The median enrollment was 7% in majority low-SES schools and 6% in all of the following: majority high-SES schools, majority underrepresented racial/ethnic minority schools, majority underrepresented racial/ethnic majority schools, majority female schools, and majority male schools.

The present study was an independent, stand-alone randomized controlled trial embedded within a larger "horserace" megastudy. That is, we took the opportunity to evaluate the effectiveness of our intervention by participating in a larger study that comprised a single control group and five separate treatment arms, each of which employed a different interventional strategy. The goal of the comprehensive megastudy was to assess the effect of each treatment arm on a common set of outcomes. The research teams that contributed each of the treatment arms were also given the opportunity to measure outcomes that were specific to their intervention approach, and to test separate related research questions. For example, one of the treatment arms focused on getting teachers to prompt students to independently think about possible connections between different concepts taught in the course. Another treatment arm focused on motivating teachers to support their students' ability to express their full authentic selves within the course.

The initial targeted sample for the megastudy was 1,190 teachers and their 42,127 students. Twenty targeted teachers (and their 901 students) were excluded from the study because they had been recruited to assist with research and development of the intervention arms prior to the study and were not randomly assigned to condition but instead were allowed to choose an intervention arm to complete. The remaining 1,170 teachers were randomly assigned to complete one of the experimental modules (i.e., intervention or control activity), and 273 teachers (and their 8,733 students) never began the module and were therefore excluded from the sample because they had zero exposure to any randomized content. This left a final sample of 897 teachers. A total of 321 additional students were excluded from the analytic sample because they withdrew from the course before their instructor was exposed to the experimental module, and their withdrawal status therefore could not possibly have been caused by their teacher's assignment to a treatment or control condition. This left a final analytic sample of 32,172 students nested within 897 teachers.

The 897 teachers in the sample were in one of 330 schools within one of 169 school districts in a southern state (note that we were missing school and district information for 5 teachers). Among the 897 teachers in the sample, 535 (60%) were female; 286 (32%) were Black, Hispanic/Latinx, Native American, or Pacific Islander; 385 (43%) had earned a Master's degree or higher; 312 (35%) were teaching a dual-enrollment course within the partnering PD network for the first time; 601 (67%) were teaching a course in a STEM field; and 277 (31%) were teaching in an urban school.

Among the 32,172 students in the sample, 18,082 (57%) were female (13,914 were male and 176 did not identify as male or female); 19,681 (61%) were Black, Hispanic/Latinx, Native American, or Pacific Islander; and 15,049 (47%) were from low-SES families (i.e., neither parent had earned a bachelor's degree).

Procedure. This study was conducted in the 2020-21 school year. Prior to the beginning of the fall term, teachers completed a baseline survey in which they reported several beliefs and attitudes, including their growth mindset beliefs about students. A total of 181 teachers (35 in the growth mindset–supportive teaching intervention condition and 40 in the control condition) did not complete this measure.

Teachers were then randomly assigned to condition using Random.org with equal probabilities of selection. Teachers were assigned to a control condition (in which teachers learned about ensuring learning accessibility for students) or one of five treatment conditions in a fully between-subjects "megastudy" design. The present paper focuses on the effects of the growth mindset–supportive teaching intervention arm, but a forthcoming paper will provide a comprehensive report of all results from the megastudy. Details on the four other treatment arms can be found in the study registration and in *SI Appendix* (pg. 15).

Between October 26 and November 15, teachers completed an online PD module, the content of which was determined by condition (Table 1). Teachers spent a median of 46 min on the module, and none of the treatment arms significantly differed from control in time spent ($ps > 0.158$).

Over a 3-wk period after receiving the intervention, teachers completed a survey on which they reported their intentions to use growth mindset–supportive practices, as well as their growth mindset beliefs about students. A total of 256 teachers in the overall megastudy did not complete these measures (46 in the growth mindset–supportive teaching intervention condition, 42 in the control condition; difference between conditions is nonsignificant; see *SI Appendix*, Tables S6 and S7 for more information about missingness). At the end of the school year, we retrieved data on students' pass rates, course grades, and college credit earned from institutional records. These performance outcomes were determined approximately 6 to 7 mo postintervention. See *SI Appendix*, *Text* for measurement details.

We note that as a part of students' onboarding for their dual-enrollment course, students in all teacher conditions (including control) completed an abbreviated version of the growth mindset intervention that was tested in the National Study of Learning Mindsets (NSLM; 45). The present version was shorter than the NSLM (~15 min rather than ~45 min) because it was embedded in the context of a broader module orienting students to this course. So, students in all teacher conditions had some limited exposure to growth mindset ideas, but not as much as they would have in a full-fledged growth mindset intervention of the sort that has been evaluated in previous experiments. Although this is not a possible explanation for any differences between conditions, we mention it in the interest of providing complete contextual information for any researcher who might seek to replicate our findings.

See *SI Appendix*, *Text* for a simple report on the intervention trial following Template for Intervention Description and Replication standards and *SI Appendix*, Fig. S4 for a CONSORT diagram showing participant recruitment, allocation, and attrition for each outcome measure.

Data, Materials, and Software Availability. Anonymized data from the correlational survey study have been deposited in OSF (https://doi.org/10.17605/OSF.IO/DJWP5) (62). Data from the teacher intervention randomized controlled trial are protected by data sharing agreements with our partnering professional development network. De-identified data can be accessed on a secure server by researchers who agree to terms of data use, including required training and approvals from the University of Texas Institutional Review Board. To request access to data, researchers should contact the corresponding author(s).

ACKNOWLEDGMENTS. This research was supported by the NSF under award number 1761179, the NIH under award number R01HD084772, the Bill and Melinda Gates Foundation under award number INV-004519, and the Yidan Prize Foundation under award number 47515. This work was also supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development under award numbers P2C HD042849 and T32HD007081, awarded to the Population Research Center at The University of Texas at Austin. C.A.H. is supported by the NSF Postdoctoral Research Fellowship under award number 2004831. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NSF, the NIH, the Bill and Melinda Gates Foundation, or the Yidan Prize foundation. We thank Carol Dweck, Paul Hanselman, Meghann Johnson, and Mac Clapper for their thoughtful feedback and suggestions on earlier drafts of this manuscript. We thank Matt Giani and Rebecca Lyle for their assistance curating the data from the teacher intervention trial. Finally, we thank Mary Murphy, Meghann Johnson, and Jennifer Porter for their feedback on earlier drafts of the growth mindset–supportive teaching intervention.

Author affiliations: [a]Department of Psychology and Population Research Center, The University of Texas at Austin, Austin, TX 78712; and [b]Department of Business, Government, and Society, The University of Texas at Austin, Austin, TX 78712

1. L. Chancel *et al.*, "World inequality report 2022" (World Inequality Lab, 2022).
2. World Economic Forum, "The global social mobility report 2020: Equality, opportunity, and a new economic imperative" (World Economic Forum, 2020).
3. R. Chetty, J. Friedman, E. Saez, N. Turner, D. Yagan, "Mobility report cards: The role of colleges in intergenerational mobility" (National Bureau of Economic Research, 2017), 10.3386/w23618, 20 December 2021.
4. M. Hout, Social and economic returns to college education in the United States. *Annu. Rev. Sociol.* **38**, 379–400 (2012).
5. P. Tough, *The Inequality Machine: How College Divides Us* (Mariner Books, 2021).
6. E. A. Canning, E. Ozier, H. E. Williams, R. AlRasheed, M. C. Murphy, Professors who signal a fixed mindset about ability undermine women's performance in STEM. *Soc. Psychol. Pers. Sci.* **13**, 927–937 (2022).
7. S.-J. Leslie, A. Cimpian, M. Meyer, E. Freeland, Expectations of brilliance underlie gender distributions across academic disciplines. *Science* **347**, 262–265 (2015).
8. E. A. Canning, K. Muenks, D. J. Green, M. C. Murphy, STEM faculty who believe ability is fixed have larger racial achievement gaps and inspire less student motivation in their classes. *Sci. Adv.* **5**, eaau4734 (2019).
9. M. C. Murphy, S. A. Fryberg, L. M. Brady, E. A. Canning, C. A. Hecht, Global mindset initiative paper 1: Growth mindset cultures and teacher practices (Yidan Prize Foundation, 2021), 25 August 2021, Available at SSRN: https://ssrn.com/abstract=3911594.
10. C. J. Bryan, C. A. Hecht, D. Blazar, M. A. Kraft, O. J. Solheim, Global mindset initiative working paper 2: Designing an intervention to motivate growth mindset-supportive teaching practices (*Yidan Prize Foundation*, 2021), 26 August 2021, Available at SSRN: https://ssrn.com/abstract=3911995.

11. A. L. Kroeber, C. Kluckhohn, "Culture: A Critical Review of Concepts and Definitions" in *Papers of the Peabody Museum of Archaeology and Ethnology* (Harvard University, 1952), vol. 47, pp. 7–223.
12. S. Sabarwal, M. Abu-Jawdeh, R. Kapoor, Teacher beliefs: Why they matter and what they are. *World Bank Res. Obs.* **37**, 73–106 (2022).
13. C. A. Hecht, C. S. Dweck, M. C. Murphy, K. M. Kroeper, D. S. Yeager, Efficiently exploring the causal role of contextual moderators in behavioral science. *Proc. Natl. Acad. Sci. U.S.A.* **120**, e2216315120 (2023).
14. K. M. Kroeper, A. C. Fried, M. C. Murphy, Towards fostering growth mindset classrooms: Identifying teaching behaviors that signal instructors' fixed and growth mindsets beliefs to students. *Soc. Psychol. Educ.* **25**, 371–398 (2022).
15. K. M. Kroeper, K. Muenks, E. A. Canning, M. C. Murphy, An exploratory study of the behaviors that communicate perceived instructor mindset beliefs in college STEM classrooms. *Teach. Teach. Educ.* **114**, 103717 (2022).
16. K. L. Sun, The role of mathematics teaching in fostering student growth mindset. *J. Res. Math. Educ.* **49**, 330–355 (2018).
17. C. A. Hecht, D. S. Yeager, C. S. Dweck, M. C. Murphy, "Beliefs, affordances, and adolescent development: Lessons from a decade of growth mindset interventions" in *Advances in Child Development and Behavior* (Elsevier, 2021), pp. 169–197.
18. A. Rattan, C. Good, C. S. Dweck, "It's ok—Not everyone can be good at math": Instructors with an entity theory comfort (and demotivate) students. *J. Exp. Soc. Psychol.* **48**, 731–737 (2012).
19. P. Black, D. Wiliam, Developing the theory of formative assessment. *Educ. Asse. Eval. Acc.* **21**, 5–31 (2009).
20. L. Festinger, *A Theory of Cognitive Dissonance* (Stanford University Press, 1957).
21. E. Aronson, "The theory of cognitive dissonance: A current perspective" in *Advances in Experimental Social Psychology* (Elsevier, 1969), pp. 1–34.
22. C. S. Dweck, E. L. Leggett, A social cognitive approach to motivation and personality. *Psychol. Rev.* **95**, 256–273 (1988).
23. C. S. Dweck, D. S. Yeager, Mindsets: A view from two eras. *Perspect. Psychol. Sci.* **14**, 481–496 (2019).
24. D. L. Ball, D. K. Cohen "Developing practice, developing practitioners: Toward a practice-based theory of professional education" in *Teaching as a Learning Profession*, G. Sykes, L. Darling-Hammond, Eds. (Jossey-Bass, 1999), pp. 3–34.
25. D. K. Cohen, *Teaching and Its Predicaments* (Harvard University Press, 2011).
26. A. Jacob, K. McGovern, "The mirage: Confronting the hard truth about our quest for teacher development" (TNTP, 2015).
27. K. S. Yoon, T. Duncan, S.W.-Y. Lee, B. Scarloss, K. L. Shapley, "Reviewing the evidence on how teacher professional development affects student achievement" (Regional Educational Laboratory Southwest, 2007).
28. C. J. Bryan, "Values-alignment interventions: An alternative to pragmatic appeals for behavior change" in *Handbook of Wise Interventions* (The Guilford Press, 2020), pp. 259–285.
29. C. J. Bryan *et al.*, Harnessing adolescent values to motivate healthier eating. *Proc. Natl. Acad. Sci. U.S.A.* **113**, 10830–10835 (2016).
30. C. J. Bryan, D. S. Yeager, C. P. Hinojosa, A values-alignment intervention protects adolescents from the effects of food marketing. *Nat. Hum. Behav.* **3**, 596–603 (2019).
31. E. Stice, H. Shaw, C. N. Marti, A meta-analytic review of obesity prevention programs for children and adolescents: The skinny on interventions that work. *Psychol. Bull.* **132**, 667–691 (2006).
32. C. Adelman, *The Toolbox Revisited: Paths to Degree Completion from High School through College* (U.S. Department of Education, 2006).
33. J. M. Carroll, C. Muller, E. Grodsky, J. R. Warren, Tracking health inequalities from high school to midlife. *Social Forces* **96**, 591–628 (2017).
34. D. Allen, "Dual enrollment: A comprehensive literature review & bibliography" (CUNY Collaborative Programs, Office of Academic Affairs, 2010).
35. A. Shivji, S. Wilson, "Dual enrollment: Participation and characteristics" (Data Point: U.S. Department of Education, 2019).
36. N. Thomas, S. Marken, L. Gray, L. Lewis, "Dual credit and exam-based courses in US public high schools: 2010–11" (First Look: U.S. Department of Education, 2013).
37. S. W. Hemelt, T. Swiderski, College comes to high school: Participation and performance in Tennessee's innovative wave of dual-credit courses. *Educ. Eval. Policy Anal.*, 10.3102/01623737211052310 (2021).
38. B. R. Braams, A. C. K. van Duijvenvoorde, J. S. Peper, E. A. Crone, Longitudinal changes in adolescent risk-taking: A comprehensive study of neural responses to rewards, pubertal development, and risk-taking behavior. *J. Neurosci.* **35**, 7226–7238 (2015).
39. R. E. Dahl, N. B. Allen, L. Wilbrecht, A. B. Suleiman, Importance of investing in adolescence from a developmental science perspective. *Nature* **554**, 441–450 (2018).
40. D. S. Yeager, R. E. Dahl, C. S. Dweck, Why interventions to influence adolescent behavior often fail but could succeed. *Perspect. Psychol. Sci.* **13**, 101–122 (2018).
41. G. M. Walton, The new science of wise psychological interventions. *Curr. Dir. Psychol. Sci.* **23**, 73–82 (2014).
42. D. S. Yeager, G. M. Walton, Social-psychological interventions in education: They're not magic. *Rev. Educ. Res.* **81**, 267–301 (2011).
43. J. Aronson, C. B. Fried, C. Good, Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. *J. Exp. Soc. Psychol.* **38**, 113–125 (2002).
44. P. M. Gollwitzer, Implementation intentions: Strong effects of simple plans. *Am. Psychol.* **54**, 493–503 (1999).
45. F. Foliano, H. Rolfe, J. Buzzeo, J. Runge, D. Wilkinson, "Changing mindsets: Effectiveness trial" (Education Endowment Foundation, 2019).
46. T. Porter *et al.*, Growth mindset intervention delivered by teachers boosts achievement in early adolescence. *Psychol. Sci.* **33**, 1086–1096 (2022).
47. P. R. Hahn, J. S. Murray, C. M. Carvalho, Bayesian regression tree models for causal inference: Regularization, confounding, and heterogeneous effects (with discussion). *Bayesian Anal.* **15**, 965–1056 (2020).
48. V. Dorie, J. Hill, U. Shalit, M. Scott, D. Cervone, Automated versus do-it-yourself methods for causal inference: Lessons learned from a data analysis competition. arXiv [Preprint] (2017). https://doi.org/10.48550/arXiv.1707.02641 (Accessed 20 September 2019).
49. A. Gelman, The problems with p-values are not just with p-values. *Am. Stat.* **70**, 1–2 (2016).
50. B. B. McShane, D. Gal, A. Gelman, C. Robert, J. L. Tackett, Abandon statistical significance. *Am. Stat.* **73**, 235–245 (2019).
51. D. S. Yeager *et al.*, Teacher mindsets help explain where a growth-mindset intervention does and doesn't work. *Psychol. Sci.* **33**, 18–32 (2022).
52. D. S. Yeager *et al.*, A national experiment reveals where a growth mindset improves achievement. *Nature* **573**, 364–369 (2019).
53. C. J. Bryan, D. S. Yeager, J. O'Brien, Replicator degrees of freedom allow publication of misleading failures to replicate. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 25535–25545 (2019), 10.1073/pnas.1910951116.
54. G. Gigerenzer, Mindless statistics. *J. Socio Econ.* **33**, 587–606 (2004).
55. J. P. Simmons, L. D. Nelson, U. Simonsohn, False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychol. Sci.* **22**, 1359–1366 (2011).
56. S. M. Dynarski, "For better learning in college lectures, lay down the laptop and pick up a pen" (The Brookings Institution, 2017). (6 March 2018).
57. C. J. Hill, H. S. Bloom, A. R. Black, M. W. Lipsey, Empirical benchmarks for interpreting effect sizes in research. *Child Dev. Perspect.* **2**, 172–177 (2008).
58. E. Hanushek, Valuing teachers: How much is a good teacher worth? *Educ. Next* **11**, 40–45 (2011).
59. M. A. Kraft, Interpreting effect sizes of education interventions. *Educ. Res.* **49**, 241–253 (2020).
60. A. E. Iancu, A. Rusu, C. Măroiu, R. Păcurar, L. P. Maricuțoiu, The effectiveness of interventions aimed at reducing teacher burnout: A meta-analysis. *Educ. Psychol. Rev.* **30**, 373–396 (2018).
61. D. C. Lortie, *Schoolteacher: A Sociological Study* (University of Chicago Press, 2002).
62. C. A. Hecht, C. J. Bryan, D. S. Yeager, Data, syntax, and registration repository for "A values-aligned intervention fosters growth mindset-supportive teaching and reduces inequality in educational outcomes". Open Science Framework. https://doi.org/10.17605/OSF.IO/DJWP5. Deposited 23 May 2023.
63. J. Hill, A. Linero, J. Murray, Bayesian additive regression trees: A review and look forward. *Annu. Rev. Statist. Appl.* **7**, 251–278 (2020).