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# A Growth Mind-Set Intervention Improves Interest but Not Academic Performance in the Field of Computer Science

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## Abstract

We investigated whether a growth mindset intervention could be leveraged to promote performance and interest in computer science, through what mechanisms it might do so, and whether effects were stronger for women than for men. In particular, we explored whether the growth mindset intervention improved academic performance and career interest by increasing intrinsic value. We developed and tested a scalable, online, 4-session growth mindset intervention at 7 universities, across 16 introductory computer science classes ($N = 491$). The intervention did not have a significant total effect on academic performance, although it indirectly improved grades via value. Additionally, the intervention, relative to the control, improved interest in the field and value also mediated this effect. Counter to expectations, the intervention worked equally well for women and men. Theoretical and practical applications are discussed.

## Keywords

growth mindsets, interventions, performance, career interest, computer science

In recent years, there is increasing interest in the potential of scalable psychological interventions to improve academic achievement (Walton, 2014). One type of these interventions—growth mindset interventions—focuses on cultivating the belief that students' general intellectual ability can be developed (e.g., Aronson, Fried, & Good, 2002). Although growth mindset interventions often impact academic achievement (e.g., Blackwell, Trzesniewski, & Dweck, 2007), some studies report null results (e.g., Sriram, 2014). Additionally, two recent meta-analyses highlight the small effect size linking growth mindsets to academic performance (Costa & Faria, 2018; Sisk, Burgoyne, Sun, Butler, & Macnamara, 2018). This may be, in part, because mindset interventions are postulated to be more effective within certain subpopulations such as at-risk youth (Paunesku et al., 2015). In the current work, in addition to investigating the oft-studied questions of whether and for whom growth mindset interventions work to improve classroom performance, we also investigate if growth mindset interventions can be leveraged to foster students' interest in academic fields. And, we suggest that mindset interventions work, in part, because they increase intrinsic value.

We tested these ideas in computer science, an academic domain that is increasingly important in our society, especially in terms of job growth. For example, the U.S. Bureau of Labor Statistics predicts that there will be nearly 350,000 computing-related jobs through 2026, with only approximately 60,000 graduates to fill those jobs (The Market for Computing Careers, 2018). The gap is not limited to the United States, with job growth in computer science exploding globally (Patel, 2015). This demand-supply gap raises the question of how to increase students' interest, a critical component of long-term dedication to an academic field and thus an outcome that may be as important as academic performance (e.g., Maltese & Tai, 2010).

In summary, we sought to answer three main questions. First, do mindset interventions improve academic achievement and can they also be leveraged to increase interest in the field of computer science? Second, for whom do they work best? Third, how do they work? We answered these questions by developing and testing a growth mindset intervention delivered in 16 introductory computer science classes at 7 colleges and universities across the United States.

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## Mind-Set Approach

Mindset interventions are grounded in the rich literature on implicit theories, which are knowledge structures about the malleability of an attribute such as intelligence and personality that organize the way people ascribe meaning to events. Research on implicit theories distinguishes between two main beliefs or mindsets: an incremental or growth mindset and an entity or fixed mindset (Dweck & Leggett, 1988; Dweck, 2000). Those with growth mindsets believe that human attributes are malleable and therefore can be cultivated through hard work, good strategies, and support from others. In contrast, those with fixed mindsets believe that human attributes are fixed and therefore cannot be developed, regardless of the effort expended or strategy employed. Research finds that (a) people can hold different mindsets in different domains (e.g., intelligence in general versus computer science in particular) and (b) effects are typically stronger for domain-specific assessments (e.g., programming aptitude beliefs predicted software development practice more strongly than mindsets of intelligence; Scott & Ghinea, 2014). Regardless of domain, growth (vs. fixed) mindsets are linked to self-regulatory processes that predict goal achievement (Burnette, O'Boyle, VanEpps, Pollack, & Finkel, 2013).

## Mindset Interventions

Given the links between growth mindsets and self-regulatory strategies that promote success, researchers investigated whether interventions designed to cultivate growth mindsets could promote academic performance. Although growth mindset interventions can improve academic achievement (e.g., Aronson et al., 2002), a few studies reveal null effects (e.g., Donohoe, Topping, & Hannah, 2012; Saunders, 2013; Sriram, 2014). Thus, our first goal was a conceptual replication examining whether a growth mindset intervention improved students' grades in their introductory computer science classes. Additionally, we extend the literature by investigating whether growth mindset interventions could also be leveraged to foster interest. We focus on computer science specifically because of the dearth of qualified employees. Although computing enrollments have recently risen (Zweben & Bizot, 2016), there is still a serious shortage of graduates per year (National Science Foundation, 2015). This need for qualified employees raises the issue of how to increase students' desire to continue in the major and get a job in the field—what is often called career interest (e.g., Lent, Brown, & Hackett, 1994; Saddler, Sonnert, Hazari, & Tai, 2012). A fundamental predictor of interest in a discipline is one's evaluation of potential for mastery of the subject (Eccles, 2005). We suggest growth mindsets encapsulate these expectations. For example, middle school students' growth mindsets about science ability correlated positively with whether they thought they could become a scientist (Hill, Corbett, & Rose, 2010).

Our second goal was to explore for whom the interventions work best. Growth mindsets are postulated to matter most in times of ego-threats (Burnette et al., 2013). For example, a growth mindset intervention had a stronger effect on math grades for female students than male students (Good, Aronson, & Inzlicht, 2003). Furthermore, whereas messages that "math ability is fixed" and that "women have less of the fixed ability than men" work together to diminish women's intent to remain in math, a growth mindset message can buffer against these adverse consequences (Good, Rattan, & Dweck, 2012; also see Murphy, Steele, & Gross, 2007). In the context of the current work, the growth mindset intervention may be especially impactful on academic outcomes for women as they are stereotyped as having less innate talent than men in science, technology, engineering and mathmatics (STEM) fields and tend to experience detrimental effects due to this threat (e.g., Cheryan, Plaut, Davies, & Steele, 2009; Good et al., 2012; Leslie, Cimpian, Meyer, & Freeland, 2015).

Our final goal was to shed light on one of the mechanisms that link growth mindsets to improved academic outcomes. We focus on intrinsic value—more specifically, whether one identifies with the subject (i.e., belonging) and likes the subject (i.e., enjoyment; Eccles & Wigfield, 2002)—because growth mindsets send a potent and implicit message that anyone can belong to a field and that learning about it is valuable. In support of these claims, research highlights the importance of growth mindsets for academic belonging (Good et al., 2012; Murphy & Dweck, 2010). Furthermore, students with growth, relative to fixed, mindsets report valuing learning more (Dweck, 2000) and report more positive attitudes regarding their academic endeavors (Aronson et al., 2002). And, these evaluations of belonging and enjoyment are critical for academic outcomes. For example, achievement motivation theory highlights the importance of value for persistence and performance (Eccles & Wigfield, 2002). Similarly, social cognitive career theory underscores how people form an enduring interest in an activity when they anticipate that performing it will be of value (Lent & Brown, 1996; Lent et al., 1994). Thus, we postulate that intrinsic value will mediate the intervention to academic outcomes links. Building on the preceding theoretical analysis, we hypothesize the following:

1. A growth mindset intervention, relative to the control, will lead to stronger growth mindsets (manipulation check).
2. A growth mindset intervention, relative to the control, will improve students' performance and career interest in introductory computer science classes.
3. The intervention effects on academic outcomes will be stronger for women than men.
4. The growth mindset intervention will exhibit an indirect effect on academic outcomes via increased intrinsic value.

To test our predictions, we developed a novel growth mindset intervention that used multiple modalities and sessions to deliver the mindset message. Namely, in addition to the standard message about the malleable nature of the attribute along with a "saying is believing" activity (e.g., Aronson et al., 2002), we also taught about research related to growth mindsets and included a role model. Research investigating how to best instill a growth mindset illustrated that teaching about the benefits (e.g., people with growth mindsets know that mistakes are opportunities to learn) and including celebrity endorsements' strengthened effects (Yeager et al., 2016).

# Method

## Participants

Across 16 classes at 7 universities, 493 introductory computer science students participated in the study. Sample size was a result of professors willing to participate. Post hoc power analyses suggest we had ample power to detect medium effects. We dropped two students from analyses due to cross contamination[1], yielding a final sample of 491 students (143 women). The majority reported their ethnicity as White (68%), and the mean age was 19.38 ($SD = 1.76$). As incentives for participation, we entered all students who completed the first module into a raffle to win one of five US$100 gift cards, and participants who completed all modules were entered into another raffle to win a US$500 gift card.

## Procedure

We recruited professors willing to administer the intervention in their introductory computer science classes. Seven universities or colleges (Bucknell University, Colorado School of Mines, Elon College, College of Holy Cross, Longwood University, University of Richmond, and Virginia State University) contributed a total of 16 sections. We randomly assigned students either to the growth mindset condition ($n = 245$) or to a matched control ($n = 246$) that was similar to the intervention in terms of time, type of content, and flow of content. We administered four modules across the semester, approximately every 2 weeks[2] (see Table 1). Students in both conditions watched the modules using headphones during laboratory class time with minimal instruction from or interaction with their professor. Professors and students were blind to intervention condition.

## Description of Growth Mind-Set Intervention

The modules had a consistent four-part structure (see Table 1). First, we taught students about research related to growth mindsets. Labeling and explaining the benefits of growth mindsets can make interventions more impactful, including enhancing learning attitudes (Yeager et al., 2016). Second, we delivered a standard growth mindset message—"you can develop your computer science ability." Third, we incorporated a role model, a recent graduate working at Google, who delivered a tip for success. This tip reiterated the importance of hard work and adopting effective learning strategies. We included this component because the use of successful role models can strengthen attitude change (Crano & Prislin, 2006) and improve motivation (Morgenroth, Ryan, & Peters, 2015). Finally, at the end of each module, students participated in a "saying is believing" writing exercise used in past interventions to encourage participants to adopt the growth mindset message (e.g., Burnette & Finkel, 2012). The intervention in its entirety took approximately 25 min. However, we chose to deliver the information in short bursts (5–6 min per module) to reduce burden on professors in terms of allocated classroom time and to help hold student interest.

## Description of the Attention-Matched Control Program

Students in the attention-matched control watched modules focused on health issues relevant to students in college—these modules are similar in terms of length, style, and content to the intervention condition (see Table 1). The first module focused on lifestyle causes of obesity, the second on common signs and symptoms of depression and anxiety, the third informed students about two infections commonly seen on campus, and the fourth focused on the importance of sleep for mental health. The "College Counsel" series, as this condition was called, informed students that the goal for providing information across the four modules was to share research that could be used to improve their overall college experience. As in the intervention condition, students first received information related to the topic (e.g., research and definitions), then received a tip from a student for incorporating this information into their daily lives before being asked to write pen pal letters to younger students sharing what they learned.

## Measures

Prior to viewing any modules, participants completed the pretest assessments, including demographic information and additional measures not relevant to the present report. Pretest assessment occurred immediately before Module 1. Posttest assessment occurred immediately following Module 4, approximately 10 weeks later. In addition, we collected postwave assessments at the end of each module.

### Pretest/posttest assessments

*Growth mindsets of computer science.* We adapted established mindset measures (Dweck, 2000) to the domain of computer science by replacing the word "intelligence" with "computer science" (5 items; 1 = *strongly disagree*, 7 = *strongly agree*; $\alpha = .87$ at pretest and $\alpha = .91$ at posttest; for example, "You can learn new things, but you can't really change your basic computer science ability"). Higher numbers represent a stronger orientation toward growth mindsets of computer science.

*Career interest .* For career interest, we used 2 items (i.e., "how likely would you be to take a job in a computer science–related field" and "how likely are you to major in computer science;" at pretest, $r(489) = .81$ and at posttest $r(370) = .82$. We combined the 2 items, with higher numbers representing greater interest in pursuing computer science as a career, for example, 1 = *very unlikely* and 7 = *very likely.*

**Table 1.** Description of Intervention and Control Condition Modules.

| Module | Content | Speaker | Min | Semester Week | Sample Size | Example Quotes |
|---|---|---|---|---|---|---|
| Growth Mind-Set Intervention Modules | | | | | | |
| Module 1: Introduction to mind-sets | Computer science growth message | White Female Professor | 1 | Administered Weeks 2–3 | $N = 491$ Growth $n = 245$ Control$n = 246$ | *Some people think that you have computer science talent or you don't. But the truth is that these abilities are developed.* |
| | Definition of fixed versus growth mind-sets and examples | | 5 | | | *People in a fixed mind-set believe that abilities are fixed. Everyone has a certain amount and that's that. People in a growth mind-set believe that abilities can be developed.* |
| | Learning takes time and effort | Student | 1 | | | *I really like that Albert Einstein said he wasn't smarter than other people he just spent longer on things.* |
| Module 2: Goal Setting | Computer science growth message | White Male Professor | 1 | Administered Weeks 4–5 | $N = 424$ (13.6% drop) Growth $n = 218$ Control $n = 206$ | *Computer science is just a learned set of skills. Students with this growth mind-set are motivated to seek challenges and put forth the effort to learn. Students who focus on improving their computer science abilities outperform those students who are just focused on grades.* |
| | Goal setting and mind-sets | | 3 | | | *Individuals with the growth mind-set are much more likely to focus on developing their skills. Within the growth mind-set, success is about stretching your limits and seeking new opportunities. In contrast, individuals with a fixed mind-set focus on proving their innate ability.* |
| | Focus on learning | Student | 1 | | | *I didn't spend time worried about proving my ability or looking smart. Instead I focused on learning from homework assignment and lab projects.* |
| Module 3: Goal operating strategies | Computer science growth message | Hispanic Male Professor | 1 | Administered weeks 6–7 | $N = 387$ (19.1% drop) Growth $n = 199$ Control $n = 198$ | *Initially, I was one of those students who thought that a person either has computer science abilities or does not. However, as you have been learning, boy was I ever wrong. As I developed friendships with a diverse network of computer scientists, I realized that it was hard work and perseverance that made these people successful scientists.* |
| | Growth and fixed mind-sets and beliefs about effort | | 4 | | | *Individuals with a fixed mind-set look a lot like Calvin in comic.*<br>*Calvin asks Susie: "What are you doing"*<br>*She replies: "I wasn't sure I understood this chapter so I reviewed my notes from the last chapter and now I'm re-reading this."*<br>*Calvin, in shock, then exclaims: "you do all that work???"*<br>*Susie says: "well, now I understand it"*<br>*Walking off Calvin notes, "Huh! I used to think you were smart"* |
| | Strategies for tackling difficult tasks | Student | 1 | | | *Reaching out to others and learning what worked for them really helped me achieve my goal.* |
| Module 4: Goal monitoring | Computer science growth message | Black Female Educator | 1 | Administered Weeks 9–11 | $N = 376$(23.4% drop) Growth $n = 190$ Control$n = 186$ | *I speak from experience in the field. At Amplify, I work on finding technology solutions for educators to enhance their teaching. Along my path to this position, I learned to work hard and to take the support of others.* |
| | Setbacks and mind-sets | | 3 | | | *We all face setbacks and failures. These are often a result of not putting in adequate time and effort and/or using inadequate strategies. It is important to think of failure as new information. That is, it can tell you what is not working.* |
| | Receiving feedback | Student | 2 | | | *I realize that when Computer Science professors gave me critical feedback, it did not mean that they looked down on me or that I wasn't cut out for CS.*<br>*Rather it's the opposite: these professors were holding me to high standards of success. This feedback proved very useful. It helped me to master more difficult CS material.* |
| Control Condition: College Counsel Modules | | | | | | |
| Module 1: Physical Health: Obesity | Importance of a healthy body weight | White Female Speaker | 1 | Administered weeks 2–3 | $N = 491$ Growth $n = 245$ Control $n = 246$ | *One important indication of physical health is maintaining a healthy body weight for your height, age, and gender.* |
| | Adverse effects of obesity | | 5 | | | *This disease is most alarming due to the co-morbidities associated with it including cardiovascular disease, type 2 diabetes, and osteoarthritis. Obesity is also associated with respiratory problems that can result in sleep apnea, hypoventilation, arrhythmias, and eventual cardiac failures.* |
| | Body mass index | Student | 2 | | | *I'll be teaching you how to calculate your BMI for yourself.* |
| Module 2: Mental Health: Depression and Anxiety | Importance of mental health | White Male Professor | 1 | Administered Weeks 4–5 | $N = 424$ (13.6% drop) Growth $n = 218$ Control $n = 206$ | *In a recent survey, college students themselves reported depression and anxiety to be the most prevalent obstacles to academic success.* |
| | Definition of depression and anxiety | | 5 | | | *Almost one third of college students reported a feeling of depression so severe that it was difficult to function, according to a 2011 American College Health Association Survey.* |
| | Strategies for students | Student | 1 | | | *When I have a night of studying ahead of me, I find it helpful to take a small break every two hours even if the break is just to go talk to a friend of mine.* |
| Module 3: Physical Health: Sickness | Sickness in College | White Female Speaker | 1 | Administered Weeks 6–7 | $N = 387$ (19.1% drop) Growth $n = 199$ Control $n = 198$ | *Most colleges feature a diverse student population that carry different strains of certain infections and diseases that only affect the students from other areas that have not already been immunized.* |
| | Common infections and illnesses | | 4 | | | *Another example of an illness that affects a greater proportion of college students than the rest of the population is mononucleosis also known as glandular fever or mono. The sickness is caused by the Epstein-Barr virus, the most common virus of the herpes family.* |
| | Strategies for avoiding germs | Student | 1 | | | *Please remember to wash your hands in warm water for at least 30 seconds.* |
| Module 4: Mental Health: Importance of Sleep | Importance of sleep | White Male Professor | 4 | Administered Weeks 9–11 | $N = 376$ (23.4% drop) Growth $n = 190$ Control $n = 186$ | *During sleep, the body increases blood supply to the muscles, which allows the body to physically recover from the day's stresses, which will make you less stressed.* |
| | Long-term effects of lack of sleep | | 3 | | | *Due to sleep's important role in the consolidation of memory, lack of sleep can negatively impact your ability to retain information.* |
| | Tips to get the proper amount of sleep | Student | 1 | | | *If you find you cannot fall asleep, try spending more time outside during the day or working out.* |

**Table 2.** Means and Correlations among Pooled Imputed Variables.

| Variable | $M$ | $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. Condition | — | 491 | — | | | | | | | |
| 2. Gender | — | 491 | .08 | — | | | | | | |
| 3. Pretest ITCS | 6.05 | 491 | .05 | −.01 | — | | | | | |
| 4. Posttest ITCS | 5.63 | 491 | .13** | .09 | .46** | — | | | | |
| 5. Pretest CI | 3.95 | 491 | .07 | −.10* | .15** | .16** | — | | | |
| 6. Posttest CI | 3.93 | 491 | .13** | −.07 | .11* | .21** | .79** | — | | |
| 7. Midpoint value | 4.94 | 491 | .16** | −.11* | .36** | .37** | .60** | .60** | — | |
| 8. Final grade | 3.01 | 491 | .04 | .03 | .10* | .15* | .01 | .19** | .17** | — |

*Note.* Condition: 0 = control condition, 1 = intervention condition; Gender: 0 = men, 1 = women, ITCS = implicit theory of computer science, CI = career interest.
*$p \le .05$. **$p \le .01$.

*Performance.* We obtained final grades for 403 students (Grade Point Average range = 0.70–4.0; $M = 3.07$, $SD = 0.86$).

*Postwave assessments*

*Midpoint intrinsic value.* We assessed belonging and enjoyment after each module.[3] We used shortened assessments for efficiency. Participants completed two questions related to belonging (i.e., "I feel like I belong in computer science," and "I feel similar to other people who enjoy computer science," Cheryan et al., 2009; Cheryan, Plaut, Handron, & Hudson, 2013) and 3 items related to enjoyment (i.e., "computer science is interesting," "I like computer science," and "computer science is fun"). Although achievement motivation theory suggests belonging and enjoyment should be two subfactors of the value construct, the subscales correlated at .78. Given we did not have a priori reasoning to believe one process (belonging or enjoyment) would be stronger than the other and that parsimonious theoretically driven approaches are often more replicable and likely to generalize to other samples (e.g., Costello & Osborne, 2005), we created one assessment of intrinsic value with higher numbers representing greater value ($\alpha = .97$).

We use the average of value after each module (M1, M2, M3) to provide a midpoint assessment with no temporal overlap with constructs of interest at pre- or post-intervention. We chose and average because growth curve analyses suggest no differences in rates of change. Additionally, students in the intervention condition, relative to the control, reported higher levels of value at the end of each time point, but both conditions maintain relatively stable levels from one time point to the next[4].

## Results

We had an approximately 77% retention rate and attrition from start ($N = 491$) to finish ($N = 376$) did not differ by condition, $\chi^2 = .26$, $p = .61$. In total, 335 students completed all four modules and comparing these students to those who missed one or more modules also showed no difference by condition, $\chi^2 = .88$, $p = .35$. Following the National Research Council's (2010) recommendation, we used multiple imputation to minimize the risk of bias due to missing data.[5] This widely used procedure (Rezvan, Lee, & Simpson, 2015) is suggested for handling missing data (Schlomer, Bauman, & Card, 2010). The pattern analysis of the missing data indicated a missing at random monotone pattern. Of the 59 variables included in the imputation, 55 (93.22%) were complete; of the 491 cases, 246 (50.10%) were complete; and of the 28,969 values, 25,089 (86.61%) were complete. Five imputations were created for all individual scale items and grades using the multiple imputation function in SPSS 25 (Gottschall, West, & Enders, 2012). We used these imputations for all subsequent reported analyses.

Given that students were nested within course sections, all analyses were conducted using HLM 7.01 (Raudenbush, Bryk, & Congdon, 2013). We estimated two-level models in which the interdependence of students within each course section was controlled in the second level of the model, which also included a randomly varying intercept. Deviance tests conducted for the reported models indicated no other random effects were necessary in any of the models.

For Hypothesis 3, we planned to conduct tests of indirect effects even in the absence of a total effect as there is a relative consensus that the total effect should not be used as a gatekeeper for tests of mediation and that such effects can offer theoretical contributions (e.g., Hayes, 2009; Rucker, Preacher, Tormala, & Petty, 2011). Means and correlations for the imputed variables used in the following analyses can be found in Table 2.

**Hypothesis 1:** In support of Hypothesis 1, students in the growth mindset condition reported stronger growth mindsets at posttest ($M = 5.77$), controlling for pretest, than did students in the control condition ($M = 5.49$), $B = 0.24$, $SE = 0.10$, $t(185) = 2.48$, $p = .014$, 95% CI [0.04, 0.44], $d = 0.36$.

**Hypothesis 2:** In contrast to the first part of Hypothesis 2, the growth mindset intervention failed to significantly predict grades, $B = 0.06$, $SE = 0.08$, $t(388) = 0.81$, $p = .42$, 95% CI [−0.09, 0.22], $d = 0.07$. However, in support of the second part of Hypothesis 2, students in the growth mindset condition reported greater career interest at posttest ($M = 4.18$), controlling for pretest, than did students in the control condition ($M = 3.69$), $B = 0.28$, $SE = 0.11$, $t(462)= 2.45$, $p = .015$, 95% CI [0.06, 0.50], $d = 0.23$.

**Hypothesis 3:** To examine whether gender moderated the effects of the intervention condition on our two outcomes, we regressed each outcome onto the dummy code for condition, the dummy code for gender, and the interaction. Contrary to expectations, results indicated that the implications of the intervention for performance, $B = -0.09$, $SE = 0.19$, $t(172) = -0.471$, $p = .638$, 95% CI [−0.45, 0.28], $d = -0.07$, or career interest, $B = -0.10$, $SE = 0.24$, $t(471) = -0.412$, $p = .68$, 95% CI [−0.57, 0.37], $d = -0.04$, did not depend on gender.

**Hypothesis 4:** Total effects are reported above (see Hypothesis 2). Thus, we focus here on strength of indirect effects, also reporting links between intervention condition and mediator, and mediator and outcome. Students in the growth mindset condition ($M = 5.44$) reported greater value during the semester than did students in the control condition ($M = 4.74$), $B = 0.40$, $SE = 0.11$, $t(474) = 3.68$, $p < .001$, 95% CI [0.18, 0.62], $d = 0.34$. Next, students' reports of value significantly predicted performance, $B = 0.13$, $SE = 0.03$, $t(302) = 3.96$, $p < .001$, 95% CI [0.07, 0.19], $d = 0.46$, and career interest, $B = 0.29$, $SE = 0.06$, $t(131) = 4.87$, $p < .001$, 95% CI [0.17, 0.41], $d = 0.85$. Finally, using these effects, we calculated the confidence interval for indirect effects for both performance and career interest using RMediation 1.1.4 (Tofighi & MacKinnon, 2011), which indicated that the mediated effect was significant, albeit small, for performance, 95% CI [0.02, 0.09], and career interest, 95% CI [0.05, 0.20].

## Discussion

Do mindset interventions improve performance and can they also be leveraged to enhance interest in fields where there is an increasing need for qualified employees? For whom do they work best? Moreover, how do these mindset interventions impact important academic outcomes? To answer these questions, we developed an online, scalable, module-based intervention. The intervention included almost 500 introductory computer science students across 7 universities and 16 different professors. We employed a double-blind experimental intervention such that neither the students nor the teachers were aware of what condition the students were randomly assigned to or what predictions the researchers were testing. Furthermore, we compared the growth mindset intervention to an attention-matched control that sought to eliminate the placebo effects of receiving an intervention.

In support of Hypothesis 1, students in the growth mindset condition reported stronger growth mindsets at posttest relative to students in the attention-matched control. Furthermore, if you compare the means at each time point and rates of changes between the two groups from time point to time point, we see that the intervention impacted growth mindsets at each time period but had the strongest impact at Module 1 (see supplemental results). We failed to find support for the first part of Hypothesis 2—namely, there is no total effect of the growth mindset intervention on final grades. This calls into question our premise that growth mindsets can improve academic performance—at least directly. We do find support of the second part of Hypothesis 2. Namely, our findings suggest that mindset interventions may serve an alternative goal—increasing career interest, which is an important predictor of persistence and long-term dedication. And, in computer science, a field where there is a real dearth of qualified employees, this outcome may be every bit as important and relevant to educators as performance. Indeed, research suggests one of the primary reasons students drop out of introductory computer sciences classes is lack of motivation, not poor performance (e.g., Kinnunen & Malmi, 2006).

In terms of findings related to Hypothesis 3, the effects of the growth mindset intervention were no stronger for women relative to men. Although we replicated the main effect for gender (e.g., Shapiro & Williams, 2012; Su, Rounds, & Armstrong, 2009; Weber, 2012), with men ($M = 4.11$, $SD = 1.88$) reporting greater interest in STEM fields than women at pretest ($M = 3.63$, $SD = 1.99$), $B = -0.48$, $SE = 0.18$, $t(474) = -2.75$, $p = .006$, 95% CI [−0.83, −0.13], $d = -0.29$, we failed to find support for the idea that the growth mindset intervention would offset this.[6] This failed replication of past work (Aronson et al., 2002; Good et al., 2003) matches a recent meta-analysis that finds that although effects are stronger for students from low socieconomic status (SES) households, growth mindset interventions are no more effective for at-risk students (Sisk et al., 2018). However, definitions of risk, ego-threat, and identity-threat vary across studies. Finding ways to better describe and report the at-risk characteristics of samples is of primary importance to making progress in helping students most in need. For example, one approach might be to tackle this at the individual level with students reporting the degree of ego-threat they feel in a given situation. In summary of the current work, the growth mindset intervention did not alleviate gender gaps in terms of performance or interest.

Finally, we find support for Hypothesis 4, offering insight into one of the psychological processes driving effects of mindset interventions. Specifically, learning that computer science skills can be developed enhanced the intrinsic value such skills held for students, which in turn predicted their final grade in the class and their career interest. However, the indirect effect, especially for academic performance, is small in practical terms (.05 increase in GPA). Additionally, the design did not allow for tests of recursive mediation processes. Future work should continue to explore mechanisms to enhance intervention effectiveness.

### Practical and Theoretical Applications

Mindset interventions, like other wise psychological interventions, offer the potential to impact educational outcomes (Walton, 2014; Yeager & Walton, 2011). In this research, although we fail to move the needle on academic performance, the total effect on career interest has potential implications for increasing the pipeline as interest in the field is one of the strongest predictors of long-term dedication.(Maltese & Tai, 2010). Building on this, future research may examine ways to strengthen effects. For example, although mindset interventions like ours are focused on changing *individual* mindsets, these mindsets can also reside at the *environmental* level. In terms of academia, we are likely to see this at the departmental as well as disciplinary levels. These environmental-level implicit theories can play a powerful role in shaping people's self-perceptions, behaviors, and evaluations of others (Good et al., 2012; Murphy & Dweck, 2010). Computer science, for example, is characterized by a *culture of brilliance*, with its practitioners believing that success in the field is predominantly driven by a raw, innate ability (Leslie et al., 2015). Indeed, only 23% of students and faculty in computer science agreed, "nearly everyone is capable of succeeding in the computer science curriculum if they work at it" (Lewis, 2007). Professors may communicate this fixed belief through verbal and nonverbal behavior that de-emphasizes strategies for learning and the potential for growth and development (Rattan, Good, & Dweck, 2012). Although in the current work students report relatively strong growth mindset to start, this may not be the case at STEM-focused universities and we do see their growth mindsets decline from pretest to posttest. This is similar to recent work on implicit theories of intelligence that found theories become more entity-oriented across the semester in a sample of introductory computer science students (Flanigan, Peteranetz, Shell, & Soh, 2017). In summary, future work seeking to increase the interest and continuation of students in STEM might benefit from transforming not only individual students' mindsets but also shifting learning environments to growth-oriented ones. Much research will be required to determine how best to shift the educational environment to better embody growth mindset principles and practices, but ultimately this might be the most powerful approach.

In addition to practical applications, the current work contributes to the growing literature on mindset interventions. For example, we identified a shift in intrinsic value as an important intervening variable to improve grades and enhance career interest. We of course cannot conclude that this is the most important mediator nor can we draw causal conclusions (Fiedler, Schott, & Meiser, 2011). Thus, future work should continue to delineate the psychological as well as behavior processes driving effects. Additionally, we note that we failed to find support for Hypothesis 2 (no total effect on grades), and we fail to replicate past work suggesting mindset interventions work best for females in male-dominated fields (Hypothesis 4). The main conclusion from the current work is that mindset interventions may be better served targeting interest in the field and could improve career interest for all students, not just those facing threats.

## Limitations

Despite practical and theoretical applications, there are limitations worth noting. First, any multifaceted intervention leaves ambiguity about which component(s) of the procedure drove effects. For example, is a role model delivering a growth mindset–related tip for learning critical for shifting mindsets? Bundled interventions such as the one offered in the current work leave ambiguity about what aspect is most important. Second, educational interventions are prone to contamination because the "active" ingredients, in this case, a growth mindset message, can be difficult to confine to just students in the intervention condition. We, by necessity, assigned students at the individual level ($N = 493$), rather than by classroom ($N = 16$). Thus, students could have spoken to each other about the information they received in each module. Such contamination is difficult to discern and likely works against us as it can reduce effect size estimates, introduce bias, and decrease power (Keogh-Brown et al., 2007). Third, the students in the current work had strong growth mindsets to start and thus findings may not be generalizable. Future work should implement interventions earlier in the pipeline and/or should target populations, cultures, or disciplines known to have weaker growth mindsets to see whether effects replicate or are perhaps even stronger (see Yeager et al., 2014).

## Conclusion

We demonstrated that a computer science growth mind-set intervention, aimed at promoting the belief that domain-specific abilities can be cultivated, leads to gains in growth mind-sets, fosters career interest, increases the value placed on the field, and indirectly predicts grades. Based on our findings, if the goal is to improve student grades or to close potential gender achievement gaps, growth mind-set interventions may not be an optimal approach. However, if the goal is to increase students' desire to learn and their interest in majoring in and pursuing a career in computer science, growth mind-set interventions are a viable option. We hope this intervention serves as a first step in future work that investigates the potential for growth mind-set interventions to be leveraged to increase interest in fields with employment pipeline shortages, like computer science, especially since the jobs of the future are likely to be in these fields.

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## Supplemental Material

Supplemental material for this article is available online.

## Notes

1. These two students discussed the study in front of a research assistant at the home institution, which is how the researchers became aware. Results are the same if these two students are included.
2. Students willing to participate ($N = 157$; control condition, $n = 81$; experimental condition, $n = 76$) also completed, as part of an unrelated student project, a game 1 week after Module 4. The only assessment taken after the game are final grades. The game did not moderate the association between condition and final grades.
3. We also included the 5-item growth mind-set assessment after each module for a total of 10 items.
4. See supplemental files for growth curve and time series analyses value and growth mind-sets—the two assessments administered in the postmodule survey.
5. Results are similar with or without imputation.
6. We also see an effect on value such that women report less intrinsic value than men. There is no main effect of gender on final grades.

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