Student perceptions of instructor mindset are associated with undergraduate academic performance

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Abstract

A growth mindset of intelligence reflects the belief that intelligence is malleable. We propose that how students perceive the mindset beliefs of their professors—through verbal and nonverbal cues present in the classroom—might be a strong predictor of student academic performance. Survey and institutional data from a university-wide sample of 6,060 undergraduate students and 110 instructors across various disciplines and learning modalities revealed that students' perceptions of instructor mindset, but not their own mindset or instructor-reported mindset, were significantly associated with end-of-semester grades. Instead of trying to shift student or instructor mindset beliefs, interventions for enhancing academic performance could more effectively target situational cues—such as instructor language about ability and classroom practices—and how students understand and interpret these signals.

Introduction

Millions of dollars of federal funding and years of research have been invested in efforts to enhance growth mindset—the belief that intelligence is malleable—among K-12 and postsecondary students. However, these efforts often place the responsibility of developing growth-minded beliefs on the student, neglecting the impact of other factors such as instructors and the classroom context in shaping these beliefs. Acknowledging this broader ecological context, the present study uses a large university data set to test the hypothesis that students' perceptions of their instructors' mindset beliefs might predict student academic performance, over and above student- and instructor-reported mindset beliefs.

A belief that intelligence can grow through effort (growth mindset) is linked with improved academic outcomes, in correlational (*1*), experimental (*2-4*), and meta-analytic studies (*5*). A variety of interventions targeting mindset have also emerged in academic settings globally (*1*). However, other research has cast doubt on this link (*6, 7*), indicating that a focus on the student's own mindset might be misplaced. Evidence is beginning to emerge that a student's academic performance is not solely the result of their own mindset beliefs, but also the beliefs and behaviors possessed by key socializing agents (*8-11*). College students' beliefs about intelligence are shaped in part by their peers and the broader society (*12*). In a prominent study, college students who had STEM professors who endorsed a growth mindset of ability were more likely to earn higher grades compared to students whose professors endorsed a fixed mindset (*8*).

Yet, other studies have suggested that instructors' own self-reported mindset beliefs might not be a particularly useful predictor of student outcomes for several reasons. First, self-reports do not always match actual beliefs or associated behaviors (*13*), which might explain the heterogeneous and often inconsistent pattern of results in this area. Second, given the positive discourse around growth mindset in popular culture, with the concept becoming increasingly mainstream in academic settings globally (*14*), instructors might be primed to see themselves as growth-minded individuals, even if their actual behaviors suggest otherwise. Third, predictive models have often failed to account for the interpretations that students make about instructors' learning environments. When students engage in their courses, they make judgments about the instructor and the course based in part on the verbal and nonverbal cues they perceive in the learning environment (*15*). Statements such as "this is a weed-out class" or "everyone can succeed in this class" provide information about what the instructor is likely to believe about the nature of intelligence and ability. A syllabus that advertises tutoring programs can signal the instructor's belief that hard work and help seeking help ensure success. In contrast, instructors who selectively call on some students but not others can send an implicit message that some students are smart, while others are not. Therefore, although relatively understudied, *student perceptions of instructor mindset*—as well as the *instructor's overall mindset climate* as reflected by the aggregated perceptions held by students with the same instructor (*16*)—may predict student performance over and above students' and instructors' self-reported mindset beliefs (*17, 18*).

These cues are more salient in traditional, face-to-face delivery formats, where most of the research examining mindset has occurred. However, over the past two years of the COVID-19 pandemic, there has been a significant shift in learning and instruction to virtual and hybrid approaches (*19*). This shift might impact how students perceive and interact with their instructors. Verbal and nonverbal cues (*20*) that might be present and easily recognized in physical classrooms might be absent or opaque in virtual settings, potentially making it more difficult for students to form accurate judgments about the instructor and the course. One enduring consequence of the pandemic has been a shift to and growing embrace of virtual and hybrid learning approaches. Therefore, it is especially important to examine whether differences in learning modalities brought about by the pandemic might be shaping student mindsets and achievement in college settings.

Method

During the fall of 2020, we conducted the *Teaching and Learning During COVID-19* study to better understand the teaching and learning experiences of undergraduate students and instructors across a large research university in the United States during the height of the global pandemic. We collected survey and institutional data from 110 instructors and 6,060 undergraduate students enrolled in 150 participating courses across 12 academic units. Seventeen percent of students were part of an underrepresented racial minority group, and just over a quarter were first-generation college students. We asked the following question: Are instructor mindset beliefs at the beginning of the semester, as rated by instructors and as perceived by students, associated with student course performance at the end of the semester? We hypothesized that both instructor-reported fixed mindset and student perceptions of instructor fixed mindset would be associated with lower end-of-semester grades, after controlling for students' self-reported mindset beliefs.

Near the beginning of the semester, instructors and students completed surveys that included questions about mindsets. Instructor-reported mindset was measured using two items: "Some students are smart, while others are not" and "Students have a certain amount of ability, and they really can't do much to change it."(*8*) The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*); a composite score was calculated by taking the mean of the two items to generate a mindset score. Student perceptions of instructor mindset were measured in a parallel manner. Students answered two items about their instructor's mindset: "My instructor seems to believe that some students are smart, while others are not" and "My instructor seems to believe that students have a certain amount of ability, and they really can't do much to change it" (*21*). The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*); a composite score was calculated by taking the mean of the two items to generate a mindset score. In addition to investigating *individual student perceptions* of their instructor's ability mindset beliefs, we also created an *aggregated variable for each instructor* that reflected the average of all individual student perceptions for a given instructor. This measure is intended to reflect the <u>instructor's overall mindset climate</u> (*16*). Finally, <u>student-reported mindset</u>, which was used as a control variable, was measured using one item: "How much do you think people are able to change their intelligence?" The response scale ranged from 0 (*not at all*) to 100 (*a lot*). Student-reported mindset was reverse coded so that higher scores on all mindset variables indicated a fixed mindset. Prior to analysis, student-reported mindset was also rescaled to a 1-6 scale to facilitate comparisons across mindset variables.

A course modality variable (fully online or not fully online) captured the type of instructional modality used in the course. A course discipline variable classified whether the course was in a STEM/health-related field. Student demographic information was obtained from institutional records and included as control variables in the analysis. Student end-of-semester course grade, our primary outcome measure, was also obtained from institutional records and reported on a 0 to 4 scale.

We estimated a two-level linear mixed-effects model using the lmer command in the lme4 package in R (*22*). Students were the Level 1 units, and instructors were the Level 2 units. Data were not perfectly nested; students could take courses from multiple participating instructors, and instructors could opt into the study for multiple courses they were teaching. Therefore, crossed random effects were included to account for the data structure. Missing data were handled by listwise deletion, and restricted maximum likelihood was used in all analyses. Our prespecified significance threshold was alpha = .05. Detailed information on materials and methods are available as supplementary materials at https://osf.io/zcmq6/.

Results

Table 1 shows the regression estimates for an intercept-only model (Model 1), a model with only student-level predictors (Model 2), and the full model with all predictors (Model 3). The estimates presented in Model 3 represent our main findings, which are discussed here. Student male gender, URM status, and first-generation status were negatively associated with student grade. Student self-reported mindset beliefs were not associated with student grade ($B <$ 0.01, $p = .47$); the 95% confidence interval suggests that this is a true null effect.

Our first question was whether instructor mindset beliefs, as rated by instructors at the beginning of the semester, were associated with student course performance at the end of the semester. Contrary to our hypothesis, instructor-reported mindset was not associated with student final grades ($B = -0.01$, $p = .85$).

Our second question was whether students' perceptions of instructor mindset were associated with student course performance at the end of the semester. Supporting our hypothesis, students' individual perceptions of instructor mindset were associated with student course performance. Specifically, students who perceived their instructors as holding a more fixed mindset earned lower grades compared to students who perceived their instructors as holding a more growth mindset ($B = -0.03$, $p < .001$). We also found that a more instructor fixed mindset climate (i.e., the aggregated instructor mindset perceptions held by all students of the same instructor) was associated with lower student grades (B = -0.20, p = .03). That is, a one-unit increase in instructor fixed mindset climate resulted in a decrease of .20 GPA points on average. Because instructor mindset was measured on a 1 to 6 scale, the difference between a strongly fixed instructor mindset climate and a strongly growth instructor mindset climate is five units. If we were to observe such a difference, this would correspond to a full GPA point difference in our linear regression framework, which could be the difference between a failing grade and a passing grade. Figure 1 shows the impact of each of the mindset variables on student course grade (on a 0 to 4 scale).

None of the instructor-level covariates was associated with student grade except for course discipline: on average, the course grades of students enrolled in STEMH courses were lower than those of students in non-STEMH courses. This finding prompted a post-hoc analysis to examine possible discipline-based differences in mindset. As shown in Figure 2, a two-way ANOVA revealed no significant difference between instructor-reported mindset and student perceptions of instructor mindset in non-STEMH courses, $t(92) = 2.03$, p = .09. However, in STEMH courses, this difference was significant, with students tending to perceive their instructors' mindset as being more fixed compared to instructor-reported mindset, $t(92) = 3.18$, p = .004. In other words, there is a wider discrepancy between instructor self-reported mindset and students' perceptions of their instructors' mindset beliefs, but only in STEMH courses.

Discussion

Our results demonstrate a subtle but critical point regarding the impact of mindset on academic outcomes: When different mindset measures, demographic characteristics, and course features are simultaneously assessed, neither students' self-reported mindset beliefs nor instructors' own self-reported mindset beliefs are associated with student outcomes. Rather, student *perceptions* of their instructors' mindsets are associated with student grades. That is, students who perceive their instructors as having a more growth mindset are more likely to perform better compared to students who perceive their instructors as having a more fixed mindset. This effect is particularly powerful when examining students' aggregated perceptions of their instructors, suggesting that the overall instructor mindset climate can shape how students approach learning, which affects their subsequent academic performance.

There has been an explosion of popularity of programs and strategies designed to shape student mindset beliefs (*14*). However, our findings point to another strategy that might be useful for college-aged learners. Rather than try to shift student beliefs from a fixed mindset to a growth mindset, our results suggest that the signals that professors send, whether consciously or unconsciously—through verbal and nonverbal cues present during class, as well as statements and policies printed on the course syllabus—may matter more than self-appraisals of motivation for shaping student academic performance across different areas of study and instructional modalities. Our findings also reveal potential differences between STEMH and non-STEMH courses, suggesting that classroom cultures might also be shaped by disciplinary traditions and norms.

This study raises additional intriguing questions: What social cues about ability or intelligence are most salient for students? Are there individual differences in how students perceive and interpret these cues, and could cognitive reframing of environmental cues shape learning behaviors and academic success? Can student perceptions of their professors' mindsets change over the course of the semester, or do "first impressions" matter? Our findings demonstrate that the answer to the question "What motivates students to succeed in college?" does not reside solely within the student or the instructor. Rather, our findings indicate that the impact of mindset beliefs on student academic performance reflects a complex interaction between the individual and the environment.

Table 1

Results of linear mixed-effects models predicting student end-of-semester course grade

	Model 1			Model 2			Model 3		
	B	SE		B	SE		B	SE	
Intercept	3.49	0.04	***	3.60	0.04	***	3.76	0.10	***
Student-level variables									
Student male gender				-0.08	0.03	**	-0.08	0.03	**
Student URM status				-0.25	0.03	***	-0.26	0.03	***
Student first-generation status				-0.16	0.03	***	-0.16	0.03	***
Student fixed mindset				0.01	0.01		0.01	0.01	
Student-perceived instructor fixed mindset: Individual perceptions				-0.03	0.01	***	-0.03	0.01	***
Instructor-level variables									
Instructor male gender							-0.01	0.08	
Instructor White race							-0.11	0.09	
Instructor age							0.001	0.005	
Instructor years of teaching experience							-0.001	0.005	
Instructor tenure status							-0.02	0.10	
Course modality (fully online)							-0.01	0.06	
Course discipline (STEMH)							-0.23	0.07	***
Instructor self-reported fixed mindset							-0.01	0.03	
Student-perceived instructor fixed mindset: Aggregated perceptions							-0.20	0.09	*
Variance components									
BIC	14218			14110			14170		
N observations	5687			5687			5687		
N groups: Students	5057			5057			5057		
N groups: Instructors	94			94			94		
Random effects variance: Student	0.389			0.365			0.365		
Random effects variance: Instructor	0.089			0.086			0.067		
Random effects variance: Residual	0.328			0.331			0.331		

*p < .05, **p < .01, ***p < .001. URM: Underrepresented racial minority status. STEMH: Denotes a STEM or health-related course.

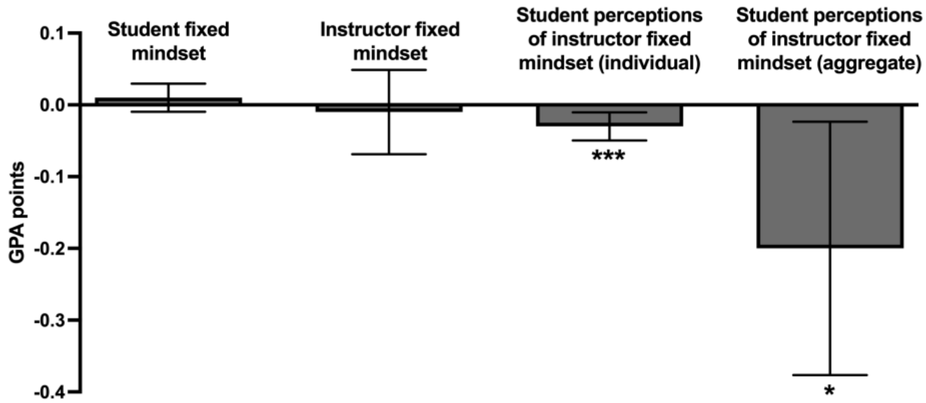

Figure 1. Impact of fixed mindset on student end-of-semester course grade. Numbers represent beta coefficients for each mindset variable, which reflect the change in course grade for each one-unit increase in the fixed mindset scales.

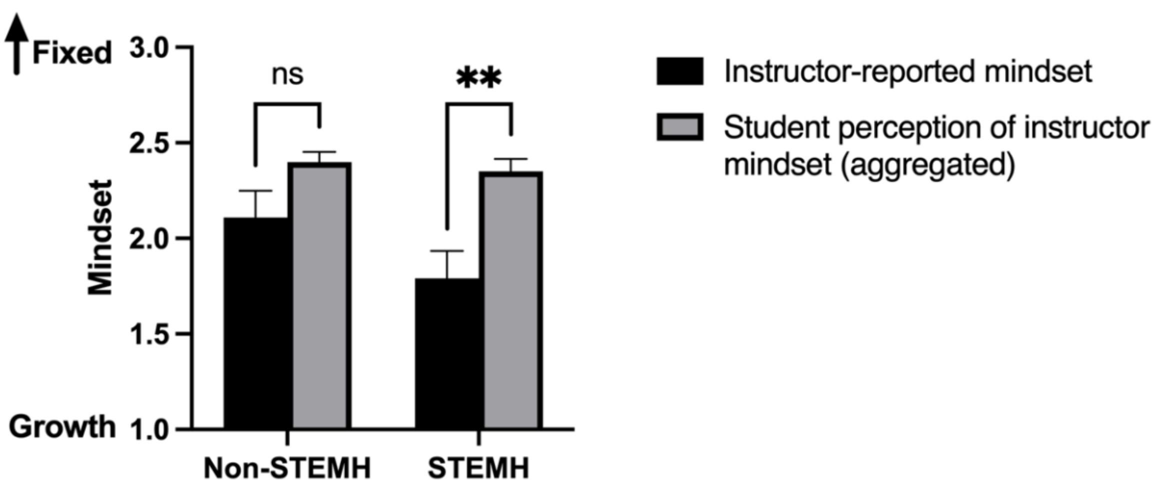

Figure 2. Ability mindset beliefs between students enrolled in a STEM or health-related field (STEMH) and non-STEMH students. Higher mindset scores indicated a more fixed mindset. A Sidak's post-hoc test was applied to control for multiple comparisons. ** $p < .01$, ns = not significant at the .05 level.

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Materials and Methods

Participants

Participants were 110 instructors and 6,060 undergraduate students (M_{age} = 20.30 years, SD = 3.5) enrolled in 150 participating courses across 12 academic units at a large public research university in the southeastern United States. Students' demographic information was obtained from institutional records. Students' race, reported by university records, was 75.6% White, 6.7% African American, 6.0% Hispanic, 2.8% Asian, 3.8% multi-racial, 0.2% American Indian or Alaskan Native, 0.1% Native Hawaiian or Other Pacific Islander, and 4.9% unknown. According to the state level agency on postsecondary education, underrepresented racial minority (URM) status was defined as Hispanic or Latino, American Indian or Alaska Native, Black or African American, Native Hawaiian or Other Pacific Islander, or Multi-racial. According to the university's classification of student by gender, the sample was 64.2% female and 35.8% male (0.03% missing). University records indicated that 26.3% of participating students were first-generation college students, defined as students whose parents or legal guardians did not earn a four-year college degree.

Instructors' demographic information was derived from the survey. Instructors' race was 79.1% White, 4.5% African American, 2.7% Hispanic, 5.5% Asian, 4.5% other and prefer not to answer, and 1.8% missing. Instructor gender was reported as 68.2% female, 28.2% male, and 3.6% missing. Instructors identified their employment status as 13.6% full professor, 14.5% associate professor, 21.8% assistant professor (tenure track), 2.7% assistant professor (non-tenure track), 20.9% lecturer, 3.6% part-time instructor, 2.7% post-doctoral scholar of fellow, 10.9% graduate student instructor, 6.4% other, 0.9% prefer not to answer, and 1.8% missing.

Procedure

The project was approved by the university's Institutional Review Board prior to instructor and student recruitment. Students were invited to complete course-specific surveys comprising closed and open-ended questions designed to assess students' academic experiences and beliefs at two time points during the Fall 2020 semester: early September and late November. Surveys were delivered via Qualtrics and took approximately 15 minutes to complete. Students were not compensated for completing the surveys, but instructors were allowed to provide extra credit to incentivize participation (students' consent status remained blinded to instructors). Some students enrolled in more than one participating course and were invited to participate in surveys for each course.

Measures

Instructor-reported mindset. Instructor-reported mindset was measured using two items: "Some students are smart, while others are not" and "Students have a certain amount of ability, and they really can't do much to change it." (*8*) The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*); a composite score was calculated by taking the mean of the two items to generate a mindset score, and Cronbach's alpha was .67.

Student perceptions of instructor mindset. Students answered two items: "My instructor seems to believe that some students are smart, while others are not" and "My instructor seems to believe that students have a certain amount of ability, and they really can't do much to change it." (*20*) The response scale ranged from 1 (*strongly disagree*) to 6 (*strongly agree*); a composite score was calculated by taking the mean of the two items to generate a mindset score, and Cronbach's alpha was .85.

Student perceptions of instructor mindset was operationalized as an individual variable (students' individual perceptions) and aggregate variable (the pooled perceptions of all students within each instructor). This was done for both conceptual and methodological reasons. Conceptually, there is a meaningful difference between how *individual students* perceive their instructors, and how students *as a group* perceive their instructor (*16*). A high correlation between individual perceptions and aggregated perceptions indicates that students are in close agreement regarding their appraisal of their instructor's ability mindset beliefs. However, a low correlation indicates that students have different perceptions of their instructor's ability mindset beliefs; in our data, these variables were only modestly correlated (r = .19). Because these distinctions may have important psychological and behavioral consequences, we used both measures. Methodologically, because students answered these items, their scores could be considered as Level 1 units. However, because the survey items pertained to their instructors, their scores could also be considered as Level 2 units. By including both variables in the model, we were able to explicitly account for variance both within and between instructors.

Student-reported mindset. Student-reported mindset was used as a control variable and was measured using one item: "How much do you think people are able to change their intelligence?" The response scale ranged from 0 (*not at all*) to 100 (*a lot*). Student-reported mindset was reverse coded so that higher scores on all mindset variables indicated a fixed mindset. Prior to analysis, student-reported mindset was also rescaled to a 1-6 scale to facilitate comparisons across mindset variables (0–16 = 1, 17–33 = 2, 34–50 = 3, 51–67 = 4, 68–84 = 5, 85–100 = 6).

Course modality. During the fall of 2020, we asked instructors to indicate the percentage of time that their courses were delivered in each of three learning modalities: fully online, hybrid, and in-person. When instructors reported that they did not have use hybrid or in-person modalities in their courses, we designed the course as *fully online*. *Hybrid* was as used as the designation for courses that were offered in-person for less than 51% of the semester, with *in-person* reflecting courses that were delivered in-person for 51%-100% of the semester. Of the participating courses, 76 (51%) were fully online, 40 (27%) were hybrid, 31 (21%) were in-person, and 3 (2%) did not report modalities. Given this distribution, we made the decision to create a binary variable to distinguish between courses taught fully online and those that included at least some in-person instruction.

Course discipline. Participating courses represented various disciplines of study. Given the prevalence of research examining mindset beliefs in STEM contexts, we wanted to examine possible differences in our results based on whether the course disciplines were STEM-related or not. We used an expanded definition of STEM to include health-related (H) disciplines given the substantial STEM-focused course content in health areas such as nursing and public health. Accordingly, we designated each course as either "STEMH" or not. Certain courses that were part of the university's core curriculum were already predefined as STEMH, as they had to do with natural, physical, and mathematical sciences. Others were predefined as humanities or social sciences courses, which did not receive the STEMH designation. Courses not part of the core curriculum were coded as STEMH or not STEMH based on academic department and course description.

Student course grade. Student end-of-semester course grade, our primary outcome measure, was obtained from school administrative records and was measured on a 0 to 4 scale.

Tables S1 and S2 present descriptive statistics and bivariate correlations for student-level and instructor-level variables, respectively. Descriptive statistics in Table S2 are reported at the instructor level, not at the classroom level. Although most instructors taught one and only one course, some instructors in our analysis sample ($N = 30$) taught more than one participating course; therefore, in the present study, the instructor-level is not identical to the classroom level. Small discrepancies in our reporting of descriptive statistics are due to this fact.

Analysis plan

To assess the appropriateness of a multilevel model, we estimated the variance in our primary outcome variable (student grade) between students (Level 1) and between instructors (Level 2) by estimating an unconditional model without any predictors (see Model 1 in Table 1). The intraclass correlation coefficient was 0.12, indicating that 12% of the variance in student grade was explained by variance at the instructor level. This non-zero number indicates that there is a strong justification for estimating a multi-level model by explicitly modeling Level 1 and Level 2 variance. Demographic information was collected and included as control variables in the analysis. Missing data were handled by listwise deletion; the final analytic sample size was 5,687 student observations. Because 590 students participated in more than one course, the number of observations (5,687) is greater than the total number of unique participants (5,057). Continuous variables (all mindset variables, instructor age, and instructor years of teaching experience) were mean centered based on the regression sample to make the intercept more interpretable.

We executed the following code in R:

```
model <- lmer(StudentGrade ~ 1 + StudentGender + StudentURM +
StudentFirstGen + StudentMindset + SPTM_Individual + InstructorGender
+ InstructorWhiteRace + InstructorAge + InstructorExperience +
InstructorTenure + CourseModality + STEMH + InstructorMindset +
SPTM_Aggregated + (1 | StudentID) + (1 | InstructorID), data = ds,
REML = FALSE)
```

In this code, we are using the lmer command to estimate a two-level model where our outcome variable student grade is predicted by our Level 1 variables (student-level covariates and student-reported mindset) and Level 2 variables (instructor-level covariates, instructor-reported mindset, student perceptions of instructor mindset, STEMH course status, and fully online course modality). Within- and between-cluster variance (random effects) are specified by (1 | StudentID) + (1 | InstructorID).

Table S1. Descriptive statistics and correlations for student-level variables.

Variable	1	2	3	4	5	6
1. Student male gender	---					
2. Student URM status	-0.00	---				
3. Student first-generation status	-0.01	**0.16**	---			
4. Student fixed mindset	**0.03**	**-0.06**	**-0.07**	---		
5. Student perceptions of instructor fixed mindset	**0.13**	0.01	-0.02	**0.03**	---	
6. Student course grade	**-0.06**	**-0.13**	**-0.10**	0.01	**-0.08**	---
n	5057	5057	5057	5057	5687	5687
M	35.4%	16.3%	26.3%	2.24	2.47	3.36
SD				1.21	1.48	0.91
Range				1-6	1-6	0-4

Note. Bolded coefficients are significant at the $p < .05$ level. Pairwise correlations use listwise deletion (n = 5,057 for gender, URM, first-generation status, and growth mindset; n = 5,687 for student perception of instructor fixed mindset and course grade). Means, standard deviations, and ranges are based on the full sample. Only means are provided for dichotomous variables.

Table S2. Descriptive statistics and correlations for instructor-level variables.

Variable	1	2	3	4	5	6	7	8	9
1. Instructor male gender	---								
2. Instructor White race	-0.18	---							
3. Instructor age	0.06	0.12	---						
4. Instructor years of teaching experience	0.00	0.15	**0.76**	---					
5. Instructor tenure status	0.04	0.04	**0.58**	**0.55**	---				
6. Course modality (fully online)	-0.13	-0.01	0.07	0.13	0.05	---			
7. Course discipline (STEMH)	-0.04	-0.03	0.08	0.16	0.00	0.07	---		
8. Instructor fixed mindset	0.14	-0.03	-0.03	-0.06	0.11	-0.04	-0.16	---	
9. Student perceptions of instructor fixed mindset (aggregated)	-0.05	-0.06	0.02	0.04	-0.19	0.04	-0.05	0.01	---
n	94	94	94	94	94	94	94	94	94
M	24.5%	81.9%	44.13	13.46	27.7%	45.7%	38.3%	1.99	2.38
SD			11.56	10.67				0.99	0.39
Range			25-77	0-48				1-5.5	1.5-3.25

Note. Bolded coefficients are significant at the $p < .05$ level. Only means are provided for dichotomous variables.

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