Math Attitudes, Engagement, and Performance of High School Students on High and Low-stakes Tests of Statistics Knowledge

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Abstract

(199 / 200 words max)

Understanding the extent engagement and math attitudes predict performance in statistics courses could inform educational interventions in this subject area, which has growing demand. We examined direct and indirect associations between course engagement-related constructs, math attitudes, and learning outcomes. Confirmatory factor analysis was used to validate scores from measures of these constructs with a sample of high school students enrolled in Advanced Placement (AP) Statistics (N = 720, *Mean age* = 16.8 years, SD = .82). Structural equation models were fitted to the data to examine relations between these constructs on a subsample (N = 220). A greater proportion of variation was explained in a high-stakes learning outcome (R^2 = .54) than a low-stakes learning outcome (R^2 = .24). We found some evidence of indirect effects of academic procrastination and course engagement on the learning outcome by way of math attitudes. The findings shed light on opportunities for intervention on academic maladaptive behaviors, such as procrastination, which could lessen negative effects on math attitudes and learning. These findings highlight the importance of testing stakes when examining associations between engagement, math attitudes, and learning, particularly in the context of high school statistics, a growing and yet understudied STEM learning context.

keywords: math attitudes; engagement; procrastination; statistics education; mediation; high- and low-stakes

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Introduction

Students' attitudes toward math are often viewed as an outcome or a predictor of math learning (Ashcraft & Krause, 2007), but to what extent does it also mediate the association between other factors and learning? Student engagement-related factors, such as course engagement (Fung et al., 2018) and academic procrastination (Kim & Seo, 2015), are also correlates of math achievement. With few exceptions (e.g., Everingham et al., 2017), prior efforts to examine the effects of math attitudes as a mediator of engagement-related factors have been limited. Although student engagement is thought to be malleable and shaped by the environment in which math learning occurs (Watt et al., 2017), it is less clear how instructional practices support or mitigate the effects of math attitudes on learning. In the present study, we examined the associations between engagement-related behaviors, math attitudes, and learning outcomes. Establishing an understanding of the associations between these constructs may provide informed instructional frameworks that enhance engagement, promote more positive orientations towards math, and increase learning.

Math Attitudes and Math Performance

While attitudes refer generally to a tendency to think, feel, perceive, and behave a certain way about something, math attitudes refer to one's predisposition to think, feel, perceive, and behave in response to the learning or application of math knowledge and skills (Neale, 1969). There appear to be both affective (e.g., lack of enjoyment, feelings of tension or fear) and cognitive (e.g., lack of self-confidence, self-deprecating thoughts, and worries) dimensions of math attitudes (Higbee & Thomas, 1999; Ho et al., 2000).

Math attitudes appear to be strongly correlated with attitudes towards science, technology, engineering, and other math-related (STEM) subject areas, particularly statistics (Baloğlu, 2002; Chew & Dillon, 2014; Paechter et al., 2017; Zeidner, 1991). Even as students become more familiar with statistics and other STEM subject areas, their prior experiences in math are likely to serve as a foundation for their attitudes about learning within the subject area. Particularly when learning new math-relevant concepts, students may draw on their past experiences in quantitative reasoning more broadly to inform beliefs about their ability. Thus, it is reasonable to expect that math attitudes correlate with performance in other STEM subject areas such as statistics. For example, a recent meta-analysis by Barroso et al. (2021) did not find evidence that the association between math-related attitudes and achievement differed when achievement outcomes were measured in math compared to statistics. Furthermore, many students are likely to have been introduced to statistics within the context of a math course (Gould, 2010; Usiskin, 2015), and thus are likely to draw from their experience and attitudes towards math when learning novel quantitative subject areas such as statistics.

Academic Engagement and Math Attitudes

The quality of students' active involvement in specific math learning tasks (i.e., their engagement) has been shown to correlate with math attitudes and learning outcomes. Some research indicates that intense engagement with math learning (e.g., through one-to-one tutoring) can reduce anxious neurological response among children in the presence of math stimuli (Supekar et al., 2015). Consistent with the three-component model for measuring attitudes (Olson & Maio, 2003), course engagement appears to comprise three dimensions that tap into affective (i.e., interest and motivation), behavioral (i.e., observable participation), and cognitive (i.e., appraisals, self-concept, and self-confidence) processes (Fredricks, 2011). Students who are affectively engaged may convey that they are driven to achieve in the subject area. In contrast, students who are behaviorally engaged may convey that they are consistent in attending the class, taking notes, completing homework, and generally participating in the course. Cognitively engaged students are likely to express that they contemplate the subject matter even when they are not expected to and willingly self-evaluate their comprehension of course material. Some past research suggests that each of these three dimensions of engagement explain variation in learning outcomes to differing degrees (Ober et al., 2021), particularly when math attitudes are taken into consideration given that they provide a frame for students' engagement-related behaviors and motivation (Goldin et al., 2011).

Academic procrastination is negatively associated with academic task engagement, although several explanations for this behavior may exist. Academic procrastination has been defined as a purposeful and unnecessary delay in starting or completing a task in an academic context coupled with problematic levels of anxiety associated with this delay (Rothblum et al., 1986). The tendency to procrastinate in an academic context may arise from a fear of academic failure combined with an anxious response to the possibility of being evaluated (Flett et al., 1995). There is evidence that the tendency to hold negative math attitudes is associated with avoidance of math tasks (Choe et al., 2019). For example, Walsh and Ugumba-Agwunobi (2002) found that students who tended to procrastinate on academic tasks were more likely to report having negative orientations towards statistics. Past research has also found that academic procrastination resulting from the fear of failure and task aversiveness was associated with dimensions of such negative orientations toward statistics among a sample of graduate students (Onwuegbuzie, 2004). However, whether such associations are present among a sample of children or adolescent students remains still largely unexamined.

Associations between Math Attitudes, Engagement, and Learning

Theoretical Perspectives

Theories on motivational processes may also provide a connection between engagement-related behaviors and math learning. According to the *expectancy-value theory* (EVT), students make appraisals about the anticipated investment and reward of completing a task according to multiple dimensions, including the perceived attainment value, intrinsic value, utility value, and appraised cost (Wigfield & Eccles, 2000). This framework explains how students who disengage from or procrastinate on a task may have high attainment values, despite having low perceived intrinsic or utility value and thus less likely to undertake the task (Wu & Fan, 2017). According to EVT, math attitudes appear to be related to the expectancies (i.e., beliefs about potential performance) and values (i.e., the reasons for attempting to perform) that lead to better performance in the subject area (Meece et al., 1990). Math attitudes are shaped by students' background (i.e., culmination of beliefs, behavioral tendencies, and past experiences) and is thought to predict future expectancies and values (Klee & Miller, 2019). Within the framework of EVT, math attitudes appear to be influenced by students' experiences and existing habits (e.g., to either procrastinate or engage in coursework) and subsequently influence future performance (Wigfield & Eccles, 2000). As such, this perspective may be especially relevant for understanding how engagement and math attitudes impact future math achievement.

Indirect Effects between Engagement-related Behaviors and Learning via Math Attitudes

The theories mentioned provide justification for viewing math attitudes as both an outcome of existing engagement-related behaviors, and a predictor of future behaviors and academic performance. However, modelling the relations between engagement-related behaviors, such as course engagement, academic procrastination, math attitudes, and performance may be complex as the constructs are clearly interrelated and likely mutual. There is evidence that math attitudes are influenced by past performance, and in turn, affects future performance via appraisals and emotions towards math (Carey et al., 2016).

Though there is still empirical research needed to support this perspective, past educational interventions have utilized this essential premise. Everingham and colleagues (2017) conducted an engagement-focused math learning intervention with first-year college students pursuing science degrees. The intervention focused on implementing improved assessment and learning support systems to enhance students' engagement through changes in interactions between instructors and students, assessment, relevancy of material, and integration of technology. Comparing existing institutional data and students' self-report data from before and after the implementation of the intervention, descriptive analyses suggest a general increase in positive math attitudes among cohorts following the intervention compared with those before the intervention. In addition, there appeared to be an improvement in math learning outcomes among those following the intervention. Although the authors do not test for a statistical mediation of course engagement on math performance by way of math attitudes, the theoretical model describes the relations between the constructs as such. Understanding this mediation may provide empirical support for interventions such as this one which focus on positive and actionable changes leading to greater engagement may be effective in reducing academic procrastination (Grunschel et al., 2018).

Examining Associations within Low- and High-Stakes Assessment Contexts

Studying the associations between math attitudes, engagement-related behaviors, and math learning outcomes is challenging given difficulty in controlling study variability in samples and assessments of learning in applied educational contexts. Within such contexts, particularly the consistency of the curriculum and the stakes associated with learning outcomes may also affect these associations. We were thus interested in examining the effects of math attitudes and engagement-related behaviors with measures derived from an authentic classroom setting, where learning outcomes associated with low- and high-stakes contexts could be considered. To do so, we investigated these factors within the context of an Advanced Placement (AP) Statistics course. AP courses offer high school students the chance to enroll in courses taught with a college-level curriculum over the span of an academic year. Courses such as AP Statistics are typically taught with consideration towards a standard set of topic areas (CollegeBoard, 2021a), and thus despite potential differences in the instructional quality between classes and schools, such courses provide a unique research context given the uniformity of instructional content.

Some growing evidence indicates that the decision to pursue a post-secondary degree in STEM disciplines is formed as early as the beginning of high school (Maltese & Tai, 2011; Sadler et al., 2012), and that completion of AP courses in STEM disciplines during high school is predictive of persistence in a STEM college program and degree attainment (Ackerman et al., 2013). Of the STEM AP course offerings, statistics is a particularly rich context to study these factors because the subject area is likely to attract students for its broad applications in fields within and outside of STEM, including business and the social sciences, among others (Garfield & Ben-Zvi, 2007). As such, many students learn statistics while completing their undergraduate degree, with some estimates indicating that 58% of students who completed a bachelor’s degree in 2008 took coursework in statistics (NCES, 2013). Furthermore, between 2009-2019, AP Statistics course enrollment appears to have grown by an average of 7% per year, suggesting that it is a steadily expanding AP program (CollegeBoard, 2021b).

Many students who enroll in AP coursework are within one to two years from high school graduation and typically intend to pursue a college degree (Judson, 2017). Students who receive a certain score or above on the AP exam, which is offered once at the end of each academic year in May, may be eligible for college credit equivalent to a semester's coursework in the subject area. As such, students who enroll are incentivized to achieve a high score on the AP exam as the grade received on it is tied to students' fulfilment of post-secondary required coursework. The AP exam is therefore a summative high-stakes exam given that it is tied to a decision (i.e., eligibility to receive college credit or not) that determines students' progress towards degree completion.

Past research has found that stressful situations, such as a high-stakes exam induce negative attitudes toward the subject matter, and under extreme circumstances, precipitate anxiety which may impair cognitive functions such as working memory and problem-solving (Beilock, 2008). According to Ashcraft and Moore (2009), there may be an increase in negative math attitudes and self-focused attention among certain students in high-stakes contexts, who thus internalize negative feedback received in response to low performance from previous high-stakes assessment contexts. Thus, students with more negative math attitudes may not perform at an optimal level on high-stakes tests such as the AP exam whereas their performance may be less affected in low-stakes contexts. Studying performance on the AP exam in comparison to performance on a low-stakes assessment thus provides a suitable applied educational context to examine differences in math attitudes, engagement, and procrastination in relation to performance. For all the reasons mentioned above, AP Statistics provides a rich and unique context to study associations between math attitudes, engagement-related behaviors, and learning outcomes.

Current Study

Based on previous work, it is evident that math attitudes have a reciprocal effect on future math learning, such that more negative math attitudes diminish future math learning, which subsequently leads to more negative future math attitudes. However, few studies have identified potential mechanisms that affect this cascading cycle. An empirical investigation examining the associations between these constructs could inform interventions that support student engagement and learning in the context of statistics courses.

It may be difficult to generalize associations between engagement-related behaviors, math attitudes, and learning when contexts for assessing achievement can substantially differ. As a first step towards generalizability, some consideration of the stakes associated with the learning outcome is important, particularly given that achievement behaviors and emotions are likely to differ between a low- and high-stakes context (von der Embse et al., 2018). By first addressing these issues in construct definition and measurement, it is thus more feasible to understand the extent to which math attitudes mediate the relations between engagement-related behaviors and learning outcomes. Furthermore, the AP course presents a unique context which may serve as an opportunity to examine students' burgeoning interest in pursuing a STEM college degree or career, as well as factors which may promote an understanding of the relation between math attitudes and statistics learning in both a low- and high-stakes testing context.

Research Aims

We examine associations between engagement, academic procrastination, and math attitudes with respect to learning outcomes among a sample of high school students enrolled in AP Statistics by attempting to address the following research questions:

- **RQ1:** Is academic procrastination and dimensions of engagement (affective, behavioral, and cognitive), measured in the fall semester, significantly and directly associated with students' AP Statistics learning outcomes, as measured at the end of the school year in a low-stakes (**RQ1a**) and high-stakes (**RQ1b**) testing?
- **RQ2:** Are the affective and cognitive dimensions of math attitudes, measured in the spring semester, significantly and directly associated with learning outcomes as measured at the end of the school year in a low-stakes (**RQ2a**) and high-stakes (**RQ2b**) testing context?
- **RQ3:** Accounting for the direct effects of each predictor, are there still significant indirect effects of procrastination and aspects of engagement on the learning outcomes as measured at the end of the school year in a low-stakes (**RQ3a**) and high-stakes (**RQ3b**) testing context, by way of the affective and cognitive dimensions of math attitudes?

We had several hypotheses about the relations between constructs. With respect to **RQ1**, we expected that academic procrastination, measured as a temporally distal predictor, would be at most weakly and negatively associated with the learning outcome. Given that we anticipated the effect to be weak, we did not expect it to differ between the high-stakes (AP exam) or low-stakes (mock AP exam) contexts. We also expected that certain aspects of engagement, particularly affective and cognitive (see Ashcraft & Moore, 2009; Goldin et al., 2011), would be more strongly and positively associated with the learning outcomes. For those dimensions of engagement which were significantly associated with the learning outcomes, we anticipated that they would generally be more strongly associated with the low-stakes learning outcome.

For **RQ2**, we anticipated that more favorable math attitudes would overall be significantly and positively associated with students' learning outcomes, though the strength of the effect may differ between the affective and cognitive dimensions of math attitudes. We additionally expected to find that the association between the two dimensions of math attitudes and the learning outcome would be greater in the high-stakes context than in the low-stakes context.

Finally, for **RQ3**, we suspected that math attitudes would partially mediate the association between certain aspects of engagement, and the learning outcome. Furthermore, we anticipated that the associations between engagement-related factors and math attitudes with respect to the learning outcomes would yield a stronger effect in a high-stakes compared with a low-stakes testing context.

The present study advances an understanding of the associations between engagement, math attitudes, and learning in several ways. One source of novelty of the current study is our focus on math attitudes as a mediating factor that is related to engagement-related behaviors including academic procrastination and dimensions of course engagement, and proficiency on tests of statistical knowledge. Another novel aspect is that we consider performance on a test in both a low- and high-stakes context.

Methods

Before examining the associations, we sought first to establish a suitable factor structure for these constructs by conducting a preliminary study, in which we confirmed the latent factor models based on theoretical descriptions of the latent constructs of interest using responses to present measures from a sample of 720 participants. The results of this preliminary study are presented in the Supplementary Materials. After establishing evidence of construct validity, we examined the direct and indirect associations between students' general tendency to procrastinate, their engagement within the context of the statistics course (consisting of affective, behavioral, and cognitive components), math attitudes, and performance on a test of statistics knowledge using responses from a sample of 220 participants that completed all measures. Both samples were comparable based on key demographic variables, including gender and race/ethnicity, to each other and the 2019 national AP Statistics participation (see Table 1 and Table A in Supplementary Materials). Data that support the findings of this study are openly available through Ober et al. (2022).

Participants

The sample included 220 ($Mean_{age}$ = 16.8 years, SD_{age} = .82; 62.3% female) high school students enrolled in an AP Statistics course from five different schools located in the North Midwest U.S. during the 2018-2019 academic year. All participants were required to have completed necessary parental consent and assent documentation prior to data collection to be eligible to participate in the study. No students actively declined to participate. Throughout the school year, participants were offered free access to the online assessment system of AP Statistics we developed. In addition to free practice questions on AP statistics, students were asked to take self-report surveys on learning-related constructs.

The demographic information is summarized in Table 1. The entire participant sample was comparable to the national student body completing the AP Statistics exam (CollegeBoard, 2021c), based on certain key demographics such as gender and race/ethnicity. Most of the students (94.8%) had completed between three to five high school math courses prior to enrolling in the AP Statistics course. The sample was predominantly White/European-American (57.9%) or Asian/Asian-American (29.7%). A relatively small percentage of students within the sample were eligible for free-or-reduced priced lunches (4.5%). Most of the sample indicated their parents had a 4-year college degree or above (93.6%).

Table 1. *Demographic information for combined samples (N = 220).*

Variable	N	Sample Percent	National AP Statistics Participants

			(2019) Percent
Gender	**220**		
Male	83	37.7	47.3
Female	137	62.3	52.7
Age (Years)	**220**		N/A
≤ 15	16	7.3	-
16	34	15.5	-
17	130	59.1	-
≥ 18	37	16.8	-
Race/Ethnicity	**160**		
Asian/Asian American	43	29.7	19.1
Black/African American	9	6.2	5.1
Hawaiian/Pacific Islander	1	0.1	0.1
White/European American	84	57.9	53.3
Hispanic/Latinx	5	3.4	16.0
Other	2	1.4	-
Multi-racial	15	9.4	4.5
Eligible for free/reduced-priced lunch	**156**		N/A
Yes	7	4.5	-
No	148	94.9	-
Prefer not to respond	1	0.6	-
Highest education of parent/guardian	**157**		N/A
Did not finish high school	3	1.9	-
High school diploma or G.E.D.	1	0.1	-
Attended some college; no degree	4	2.5	-
Associate's degree (A.A., A.S., etc.)	2	1.3	-
Bachelor's degree (B.A., B.S., etc.)	47	29.9	-
Master's degree (M.A., M.S., etc.)	54	34.4	-
Doctoral or professional degree (Ph.D., J.D., M.D., etc.)	46	29.3	-
AP Exam Score	209		
1	11	5.3	21.0
2	22	10.5	19.3
3	62	29.7	26.6
4	47	22.5	18.4
5	67	32.1	14.7

Measures

A series of self-report surveys were administered to students on two occasions during the academic year in which the participants were enrolled as students in an AP Statistics course. The descriptives for the self-report and learning outcome variables are shown in Table 2. As measures of learning outcomes, students' proficiency in statistics was assessed based on performance on a comprehensive mock exam that was appropriate for the curriculum in an AP high school or introductory college-level statistics course.

Table 2. *Item-level descriptives of scales for the total sample (N = 220).*

Construct	Item Wording	Mean (SD)	Median	Item-rest Correlation
Academic Procrastination				
Scale Total (excluding P08)		2.51 (0.79)	2.53	-
P01	I delay starting things until the last possible minute.	2.45 (1.31)	2	0.75
P02	I often don't finish tasks on time.	1.55 (0.91)	1	0.53
P03	I usually meet my own self-set deadlines. [R]	2.66 (1.15)	2	0.49
P04	Even when I know that a job needs to be done, I never want to start right away.	2.93 (1.26)	3	0.67
P05	I keep my assignments up to date by doing my work regularly from day to day. [R]	2.99 (1.32)	3	0.73
P06	If I have a number of jobs that need to be done by the end of the day, I usually get them done. [R]	2.36 (1.07)	2	0.59
P07	I don't seem to know when I need to start a job to be able to get it done on time.	2.11 (1.10)	2	0.41
*P08**	*I am often late for my classes.*	1.22 (0.62)	1	0.19
P09	I often find myself attempting to finish an assignment in the class period right before it is due.	2.09 (1.30)	2	0.60
P10	I delay starting things so long that I sometimes don't get them done by the deadline.	1.75 (1.08)	1	0.62
P11	I overestimate the amount of work that I can do in a given amount of time.	2.58 (1.28)	2	0.46
P12	I don't delay when I know that I really need to get a job done. [R]	2.66 (1.23)	3	0.60
P13	If I have an important project to do, I get started on it as soon as possible. [R]	3.08 (1.27)	3	0.66
P14	When I have a test scheduled soon, I often find myself working on other jobs instead of studying for that test.	2.94 (1.20)	3	0.52
P15	I often finish my work before it is due. [R]	2.51 (1.24)	2	0.58
P16	I get right to work at jobs that need to be done. [R]	3.03 (1.28)	3	0.70
Engagement				
Affective				
Sub-scale Total		3.30 (0.85)	3.38	-
E-A1	I am interested in learning statistics.	3.51 (1.00)	4	0.65
E-A2	I enjoy being in statistics class.	3.48 (1.07)	4	0.63
E-A3	I am motivated to learn statistics.	3.27 (1.02)	3	0.66
E-A4	My classwork makes me curious to learn other things.	3.19 (0.98)	3	0.58
E-A5	I think learning statistics is boring. [R]	3.19 (1.06)	3	0.66
E-A6	I look forward to statistics class.	3.12 (1.05)	3	0.59
E-A7	Statistics is fascinating to me. [R]	3.08 (1.06)	3	0.61
E-A8	I don't want to be in statistics class. [R]	3.59 (1.03)	4	0.65
Behavioral				
Sub-scale Total		3.65 (0.69)	3.63	-
E-B1	I study for statistics on a regular basis.	2.82 (1.13)	3	0.40
E-B2	I take good notes on the material for this class.	3.79 (1.07)	4	0.29
E-B3	I work hard to do well in this class.	3.62 (1.01)	4	0.51
E-B4	I complete my homework on time.	3.65 (1.15)	4	0.32
E-B5	I review my statistics class notes.	4.05 (0.92)	4	0.34
E-B6	I don't keep up with my grades in this class. [R]	4.03 (0.94)	4	0.44

E-B7	I pay careful attention to material from this class.	3.75 (0.93)	4	0.62
E-B8	I review my statistics assignments before turning them in.	3.50 (1.09)	4	0.46
Cognitive				
Sub-scale Total		3.41 (0.66)	3.50	-
E-C1	I try to make connections between the topics and concepts taught in this class.	3.64 (0.97)	4	0.51
E-C2	I combine ideas from different courses to help me complete my statistics assignments.	3.48 (1.06)	4	0.37
E-C3	I summarize the statistics material I learn in class.	3.21 (1.03)	3	0.44
E-C4	I identify key information from course materials.	3.73 (0.83)	4	0.56
E-C5	I monitor my strengths and weaknesses on the topics taught in statistics to better master the material.	3.58 (0.99)	4	0.47
E-C6	I discuss statistics problems that have no clear answers.	3.38 (1.08)	4	0.55
E-C7	I challenge myself to complete difficult statistics problems rather than not answer them.	3.10 (1.05)	3	0.41
E-C8	I think about the different ways to solve a statistics problem.	3.18 (1.03)	3	0.37
Math Attitudes				
Affective (Enjoyment)				
Sub-scale Total		3.20 (0.98)	3.40	-
MA-E1	I have usually enjoyed studying math in school.	3.52 (1.15)	4	0.77
MA-E2	I like to solve new problems in math.	3.41 (1.05)	4	0.74
MA-E3	I really like math.	3.28 (1.14)	3	0.78
MA-E4	I am happier in a math class than in any other class.	2.45 (1.12)	2	0.64
MA-E5	Math is a very interesting subject.	3.32 (1.16)	4	0.73
Cognitive (Self-confidence)				
Sub-scale Total		3.69 (0.85)	3.80	-
MA-C1	It makes me nervous to even think about having to do a math problem. [R]	3.78 (1.03)	4	0.66
MA-C2	Studying math makes me feel nervous. [R]	3.70 (1.06)	4	0.69
MA-C3	I am always under a terrible strain in my math classes. [R]	3.65 (1.07)	4	0.66
MA-C4	I am always confused in my math class. [R]	3.78 (0.88)	4	0.63
MA-C5	I feel a sense of insecurity when attempting math. [R]	3.51 (1.08)	4	0.65
Learning Outcomes				
Mock AP Exam		0.09 (0.48)	0.08	-
AP Exam		3.65 (1.18)	4.00	-

* Item excluded from the subsequent analysis, including scale score, final measurement model, and latent factor in the structural equation models.

Self-Report Measures

Background questionnaire. A self-report demographics questionnaire was administered which asked respondents to provide personal information such as their current age, gender, and parents' education.

Academic procrastination. A scale consisting of 16 Likert-type items, which was adapted from an existing measure created by Aitken (1982), was administered as a measure of academic procrastination. A typical question on the scale consisted of a statement (e.g., "*I delay starting things until the last possible minute*.") to which students would provide a response using a 5-point Likert scale indicating the extent to which the statement reflected their tendencies (*1 = Not at all like me, 2 = A little like me, 3 = Somewhat like me, 4 = Quite like me, 5 = Very like me*). The scale scores appeared to have acceptable reliability, Cronbach's alpha = .90 (95% CI = .89, .92).

Micro-engagement. The term "micro-engagement" is used to refer to engagement within the context of a specific course (Handelsman et al., 2005). Micro-engagement was measured with the Scale of Student Engagement in Statistics (SSE-S; Whitney et al., 2019) which consists of 24 items, with eight items each reflecting the affective, behavioral, and cognitive dimensions of engagement in statistics learning. Responses were provided using a 5-point Likert scale indicating the extent to which participants agreed with the statement (*1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree*). The scale appeared to have acceptable reliability over the entire set of 24-items, Cronbach's alpha = .90 (95% CI = .88, .92). The Cronbach's alpha for the affective engagement items only was .93 (95% CI = .92, .95), for behavioral engagement items only Cronbach's alpha was .82 (95% CI = .79, .86), and for cognitive engagement items only Cronbach's alpha was .77 (95% CI = .77, .85). The measure was administered at the same time as the procrastination scale, during November of the fall semester.

Math attitudes. Math attitudes was measured with items from the Attitudes Toward Mathematics Inventory (ATMI; Lim & Chapman, 2013). The short-form ATMI consists of 19 items reflecting the enjoyment, motivation, self-confidence, and perceived values associated with mathematics learning. Consistent with the operational definition of math attitudes mentioned previously which recognizes it as comprised of affective and cognitive dimensions, 10 selected items total with five each from the enjoyment and self-confidence scales were considered in this analysis. Responses were provided using the same 5-point Likert scale used to assess micro-engagement (*1 = Strongly Disagree, ..., 5 = Strongly Agree*). Items on each scale were negatively worded such that items from both subscales indicated enjoyment or self-confidence in mathematics. The enjoyment items reflect the affective domain of math attitudes, and the self-confidence items reflect the cognitive domain. The responses roughly reflect students' math attitudes at the end of the academic year as it was administered in May of the year in which students were enrolled in AP statistics. The scale appeared to have acceptable reliability over the entire set of 10-items, Cronbach's alpha = .92 (95% CI = .91, .93), as well as for the affective (i.e., lack of enjoyment) items only, Cronbach's alpha = .92 (95% CI = .91, .93), and for the cognitive (i.e., lack of self-confidence) items only, Cronbach's alpha = .89 (95% CI = .87, .90).

Learning Outcomes

Mock AP Practice Exam. As a measure of statistics proficiency in a low-stakes test context, we used a score from a 20-question mock AP practice exam. The mock AP practice exam was carefully developed by the research team in consultation with content experts, mimicking the content coverage of the actual AP statistics exam. The score is considered indicative of student performance in a low-stakes context as students submitted the test for completion credit in their AP Statistics course. Students' scores on the mock exam were computed based on the one-parameter logistic (1PL) model, a type of item response theory (IRT) model and ranged between –1.43 and .99 (*Mean* = .10, *SD* = .48), with higher scores indicative of better performance. The overall IRT-based reliability was .93, which was calculated according to

Andrich (1988) using the averaged squared standard errors for all test takers following (Embretson & Reise, 2000, p. 18). Of the 220 students with complete self-report data, 10 students did not take the mock AP exam score and as such their data were missing. This yielded a sample of 210 participants with complete self-report data and mock AP exam score data.

AP Exam. Students' proficiency was also measured with scores from the actual AP exam. Administered nationally on the same day to all students who wish to complete it during a particular academic year, the AP exam is scored such that values range from *1* (lowest) to *5* (highest). The AP exam score is considered high-stakes given that students who complete the test and receive a satisfactory score may be eligible to receive college credit, with a minimum score for receiving course credit typically being a 3 or greater. Within the present sample, scores ranged between 1 to 5 (*Mean* = 3.66, *SD* = 1.18, *Median* = 4, *Mode* = 5). The AP exam scores were provided to researchers by participating teachers. Compared to the national sample of students who completed the AP Statistics exam in May 2019 ($N = 219{,}392$), a greater proportion of students in the present sample appeared to receive satisfactory scores of 3 or more (sample = 84.3% v. national = 59.7%, $z = 7.21$, $p < .001$). There were 11 students who did not take the AP exam, thus yielding a sample of 209 with complete self-report data and AP exam score data.

Procedure

Intuitional Review Board approval was sought and granted before the research activities were conducted. In October 2018, participants completed a demographics questionnaire. Between November to December 2018, participants completed a series of self-report measures, including those for academic procrastination and engagement in the course. In May 2019, participants later completed the items from the math attitudes measure. Both the mock AP exam and actual AP exam were administered in May of the academic year in which students completed the AP Statistics course. Supplementary Materials provide additional details about the analysis and evaluation the model fit (see Appendix A). Details that support the validity of the measures used in the present study are available in Supplementary Materials (see Appendix B-D), in addition to information about the data cleaning procedures for the analytic sample (see Appendix C).

Results

Descriptive statistics for the self-report measures at the item-level and scale-level are shown in Table 2. Correlations among scale-level average scores and learning outcomes (see Appendix E).

Structural Equation Models

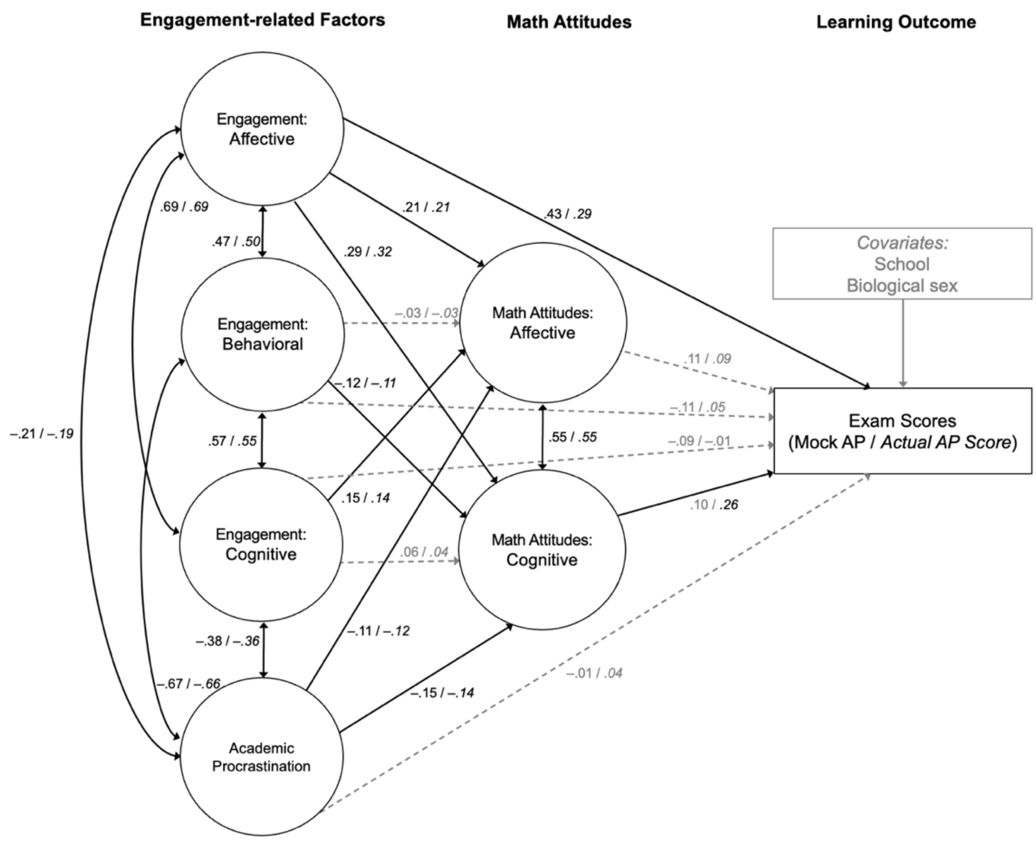

Figure 1. Structural model showing relations between constructs. Students' school (dummy coded) and biological sex (male or female) were entered into the model as a covariate.

Models were tested separately for each learning outcome (mock AP and actual AP score) and standardized estimates reflect those from the mock AP / AP score (in italics). Paths shown in dotted lines are estimated but were not significant at $p < .05$ in either model.

Analyses were conducted to address the research aims involved two separate structural equation models (SEMs). Factor loadings were constrained using the unstandardized estimates from the measurement models, thus ensuring the latent constructs in the two models were equivalent at the metric level at minimum. The first model examined the learning outcome with respect to the mock AP exam score. The second model examined the learning outcome with respect to the actual AP exam score. Figure 1 shows the structural model used in these analyses with standardized factor loadings for both SEMs. In assessing the fit of both models, fit indices were considered using the same recommended criteria mentioned earlier.

Low-stakes Test Context

We first examined the predictors with the mock AP score, a measure of statistics knowledge within a low-stakes testing context. The model demonstrated generally acceptable model fit, $\chi^2(df = 1449) = 4483.470$, $p < .001$, $CFI = .945$, $TLI = .953$, $RMSEA = .100$ (95% CI: .097, .103), $SRMR = .101$. However, we note that the χ^2 test was significant and the RMSEA and SRMR were both above the recommended thresholds. As noted previously, though significant, the χ^2 test is known to be sensitive to sample size and non-normality (Fan et al., 1999). The RMSEA and SRMR, being absolute fit indices, tend to be more sensitive to sample size and non-normality (Ainur et al., 2017), particularly when model complexity is high (Shi et al., 2019). Inspection of the modification indices suggested that model fit may be improved by adding a directional path from each of the engagement and math attitudes latent constructs to academic procrastination. We note that the latent factor for academic procrastination consisted of nearly or more than twice as many indicator variables as the other latent constructs. A greater number of indicator variables may lead to excessive power for the χ^2 goodness-of-fit tests (MacCallum et al., 1996; Moshagen, 2012), upon which the modification indices are based. Thus, the modification indices may have been biased in favor of estimating parameters associated with the academic procrastination construct. Furthermore, we did not feel that making these adjustments to the model was appropriate given that it may result in an atheoretical model that may not generalize to independent samples (Lei & Wu, 2007).

Since we found the goodness-of-fit indices to be close or within the recommended thresholds, we proceeded with model interpretation. Furthermore, all factor loadings were significant ($p < .001$) and thus misspecification of the latent factors seemed unlikely. Table 3 shows the standardized estimates and standard errors for each direct and indirect effect.

Table 3. *Standardized regression coefficients and standard errors for direct and indirect paths in the mediation model with students' mock AP score as a learning outcome (N = 210).*

Model Parameters	β (*SE*)	95% CI	*p*
Direct Effects			
Procrastination → Math Attitudes: Affective	–0.11 (0.03)	–0.17, –0.05	<.001***
Engagement: Affective → Math Attitudes: Affective	0.21 (0.03)	0.15, 0.28	<.001***
Engagement: Behavioral → Math Attitudes: Affective	–0.04 (0.04)	–0.12, 0.05	.439
Engagement: Cognitive → Math Attitudes: Affective	0.15 (0.04)	0.06, 0.23	<.001***
Procrastination → Math Attitudes: Cognitive	–0.15 (0.03)	–0.21, –0.08	<.001***
Engagement: Affective → Math Attitudes: Cognitive	0.29 (0.04)	0.22, 0.36	<.001***
Engagement: Behavioral → Math Attitudes: Cognitive	–0.12 (0.05)	–0.21, –0.03	.013*
Engagement: Cognitive → Math Attitudes: Cognitive	0.06 (0.05)	–0.04, 0.16	.252
Procrastination → Mock AP Exam	–0.01 (0.07)	–0.14, 0.13	.925
Engagement: Affective → Mock AP Exam	0.43 (0.09)	0.26, 0.60	<.001***
Engagement: Behavioral → Mock AP Exam	–0.11 (0.10)	–0.32, 0.09	.274
Engagement: Cognitive → Mock AP Exam	–0.09 (0.11)	–0.30, 0.11	.377
Math Attitudes: Affective → Mock AP Exam	0.11 (0.06)	–0.01, 0.24	.068
Math Attitudes: Cognitive → Mock AP Exam	0.10 (0.06)	–0.03, 0.22	.124
Combined Direct Effects			
Engagement (A + B + C) → Mock AP Exam	0.22 (0.07)	0.09, 0.35	<.001***
Math Attitudes (A + C) → Mock AP Exam	0.21 (0.04)	0.13, 0.29	<.001***
Latent Covariance Parameters			
Procrastination ↔ Engagement: Affective	–0.21 (0.01)	–0.23, –0.19	<.001***
Procrastination ↔ Engagement: Behavioral	–0.67 (0.01)	–0.69, –0.65	<.001***
Procrastination ↔ Engagement: Cognitive	–0.38 (0.01)	–0.40, –0.35	<.001***
Engagement: Affective ↔ Engagement: Behavioral	0.47 (0.01)	0.44, 0.49	<.001***
Engagement: Affective ↔ Engagement: Cognitive	0.69 (0.02)	0.66, 0.72	<.001***
Engagement: Behavioral ↔ Engagement: Cognitive	0.57 (0.02)	0.53, 0.61	<.001***
Math Attitudes: Affective ↔ Math Attitudes: Cognitive	0.55 (0.01)	0.52, 0.58	<.001***
Mediation Parameters			
Mediation by way of Math Attitudes: Affective			
Indirect Effects			
Engagement: Affective → Math Attitudes: Affective → Mock AP Exam	0.02 (0.01)	<.001, 0.05	0.069
Engagement: Behavioral → Math Attitudes: Affective → Mock AP Exam	<.001 (0.01)	–0.01, 0.01	0.468
Engagement: Cognitive → Math Attitudes: Affective → Mock AP Exam	0.02 (0.01)	<.001, 0.04	0.121
Procrastination → Math Attitudes: Affective → Mock AP Exam	–0.01 (0.01)	–0.03, <.001	0.094
Total Effects (Indirect Effect Plus Direct Effect)			
Engagement: Affective → Math Attitudes: Affective → Mock AP Exam	0.45 (0.09)	0.28, 0.63	<.001***

Engagement: Behavioral → Math Attitudes: Affective → Mock AP Exam	–0.12 (0.10)	–0.32, 0.09	0.258
Engagement: Cognitive → Math Attitudes: Affective → Mock AP Exam	–0.08 (0.10)	–0.28, 0.13	0.463
Procrastination → Math Attitudes: Affective → Mock AP Exam	–0.02 (0.07)	–0.16, 0.12	0.785
Combined Total Indirect Effect of Engagement			
Engagement (A + B + C) → Math Attitudes: Affective → Mock AP Exam	0.04 (0.02)	<.001, 0.08	0.074
Combined Total Effect of Engagement			
Engagement (A + B + C) → Math Attitudes: Affective → Mock AP Exam	0.26 (0.07)	0.13, 0.39	<.001***
Mediation by way of Math Attitudes: Cognitive			
Indirect Effects			
Engagement: Affective → Math Attitudes: Cognitive → Mock AP Exam	0.03 (0.02)	–0.01, 0.06	0.121
Engagement: Behavioral → Math Attitudes: Cognitive → Mock AP Exam	–0.01 (0.01)	–0.03, 0.01	0.182
Engagement: Cognitive → Math Attitudes: Cognitive → Mock AP Exam	0.01 (0.01)	–0.01, 0.02	0.376
Procrastination → Math Attitudes: Cognitive → Mock AP Exam	–0.01 (0.01)	–0.03, 0.01	0.139
Total Effects (Indirect Effect Plus Direct Effect)			
Engagement: Affective → Math Attitudes: Cognitive → Mock AP Exam	0.46 (0.09)	0.29, 0.63	<.001***
Engagement: Behavioral → Math Attitudes: Cognitive → Mock AP Exam	–0.12 (0.10)	–0.33, 0.08	0.224
Engagement: Cognitive → Math Attitudes: Cognitive → Mock AP Exam	–0.09 (0.11)	–0.30, 0.12	0.408
Procrastination → Math Attitudes: Cognitive → Mock AP Exam	–0.02 (0.07)	–0.16, 0.12	0.767
Combined Total Indirect Effect of Engagement			
Engagement (A + B + C) → Math Attitudes: Cognitive → Mock AP Exam	0.02 (0.01)	–0.01, 0.05	0.135
Combined Total Effect of Engagement			
Engagement (A + B + C) → Math Attitudes: Cognitive → Mock AP Exam	0.25 (0.07)	0.11, 0.38	<.001***
Mediation by way of Math Attitudes (Combined)			
Combined Indirect Effects			
Engagement: Affective → Math Attitudes (A + C) → Mock AP Exam	0.05 (0.01)	0.03, 0.07	<.001***
Engagement: Behavioral → Math Attitudes (A + C) → Mock AP Exam	–0.02 (0.01)	–0.03, <.001	0.091
Engagement: Cognitive → Math Attitudes (A + C) → Mock AP Exam	0.02 (0.01)	<.001, 0.04	0.025*
Procrastination → Math Attitudes (A + C) → Mock AP Exam	–0.03 (0.01)	–0.04, –0.01	<.001***
Combined Total Effects (Indirect Effect Plus Direct Effect)			
Engagement: Affective → Math Attitudes (A + C) → Mock AP Exam	0.48 (0.09)	0.31, 0.65	<.001***
Engagement: Behavioral → Math Attitudes (A + C) → Mock AP Exam	–0.13 (0.10)	–0.33, 0.07	0.210
Engagement: Cognitive → Math Attitudes (A + C) → Mock AP Exam	–0.07 (0.10)	–0.28, 0.13	0.497
Procrastination → Math Attitudes (A + C) → Mock AP Exam	–0.03 (0.07)	–0.17, 0.10	0.630
Combined Total Indirect Effect of Engagement			
Engagement (A + B + C) → Math Attitudes (A + C) → Mock AP Exam	0.06 (0.01)	0.03, 0.09	<.001***
Combined Total Effect of Engagement			
Engagement (A + B + C) → Math Attitudes (A + C) → Mock AP Exam	0.28 (0.07)	0.15, 0.41	<.001***

* $p < .05$, ** $p < .01$, *** $p < .001$

Approximately 24.1% of variance in the mock AP scores was accounted for ($R^2 = .241$) by the model paths between the learning outcome and procrastination, engagement, and math attitudes. As expected, all the covariance terms between the predictors of academic procrastination and aspects of engagement were significant and in the expected direction. Academic procrastination was negatively associated with affective, behavioral, and cognitive engagement. This indicates that students who are more likely to self–report academic procrastination behaviors are overall, across all three aspects, less likely to report being engaged in the course. Each of these three aspects of engagement were in turn significant and positively associated with each other, based on positive covariance terms, thus supporting the correlated domains perspective of engagement.

Direct associations between engagement–related behaviors and mock AP exam score. In examining the direct effects of academic procrastination and course engagement on the learning outcomes (**RQ1a**), we found that only affective engagement was directly and positively associated with performance on the mock AP exam, standardized estimate (β = .43, p < .001). This finding suggests that students who are more likely to be affectively engaged in the course are also more likely to receive a higher mock AP exam score. Neither students' self–reported academic procrastination, behavioral or cognitive engagement were significantly associated with the learning outcome directly.

We also considered combined effects (i.e.., additive effects) of certain factors on the learning outcome. Calculating the combined effects allows for the examination of the holistic effect of a multidimensional construct, such as engagement or math attitudes. The combined direct effect of affective, behavioral, and cognitive engagement was significantly and positively associated with the mock AP score (β = .22, p < .001).

Direct Associations between math attitudes and mock AP exam score. There was a direct and negative combined effect of affective and cognitive math attitudes with respect to the learning outcome (β = .21, p < .001), though neither dimension of math attitudes appeared to separately predict variation in the mock AP scores. This effect suggests that students who report having overall more positive math attitudes tend to have higher scores on the mock AP exam (**RQ2a**).

Direct associations between engagement–related behaviors and math attitudes. When math attitudes were examined as an outcome, several interesting trends emerged. Academic procrastination was negatively associated with both dimensions of math attitudes (affective: β = –.11, p < .001; cognitive: β = –.15, p < .001), such that students who indicated a greater tendency towards procrastination were more likely to report more negative attitudes toward math at the end of the semester. The affective dimension of engagement was positively associated with both affective ($\beta = .21$, $p < .001$) and cognitive math attitudes ($\beta = .29$, $p < .001$). This indicates that students who reported being more motivated tended to have more positive math attitudes. While cognitive engagement was positively associated with more favorable math attitudes ($\beta = .15$, $p < .001$), it did not appear to have an association with the cognitive dimension of math attitudes. By contrast, while behavioral engagement was not associated with affective math attitudes, it appeared to have a negative association with cognitive math attitudes ($\beta = -.12$, $p < .05$). Though it appears at first counterintuitive, affective, behavioral, and cognitive dimensions of engagement may not necessarily correlate with other factors to a similar degree or even in the same direction (Sciarra & Seirup, 2008; Wang & Degol, 2014). We return to a consideration of this finding considering research on motivation and math learning in the Discussion section.

Indirect associations with mock AP exam score. After examining the direct effects on the learning outcome of the mock AP score, we were subsequently interested in examining whether the two dimensions of math attitudes mediated the associations between the other predictors and the learning outcome (**RQ3a**). In the present model, we were able to examine mediation by way of both affective and cognitive dimensions of math attitudes separately, as well as examine the indirect and total effects of the two dimensions combined. Neither affective or cognitive dimensions of math attitudes appeared to mediate the association between engagement as a combined effect and the learning outcome.

When we examined the two dimensions of math attitudes combined as a mediator, we found there was a significant and overall positive indirect effect of affective ($\beta = .05$, $p < .001$) and cognitive ($\beta = .02$, $p < .05$) engagement on the mock AP score by way of math attitudes; however, these effects appeared to be weak based on the standardized estimate. By contrast, behavioral engagement did not appear to have a significant indirect effect on mock AP scores. In addition, there was a negative indirect effect of academic procrastination on the mock AP score by way of math attitudes was negative ($\beta = -.03$, $p < .001$).

The association between engagement and the learning outcome becomes more apparent when examining the total effect, which takes into consideration both the direct and indirect effect. Only the total effect for affective engagement on mock AP score is significant ($\beta = .48$, $p < .001$), whereas there did not appear to be a significant total effect for academic procrastination, behavioral engagement, and cognitive engagement. This finding suggests that although there is a significant direct effect of affective engagement on the learning outcome in relation to the low-stakes mock AP score, math attitudes may partially mediate this association (James et al., 2006).

While course engagement was conceptualized as a multidimensional latent construct, it has in some cases been viewed as a unitary construct (Wang & Eccles, 2012). Thus, we were interested in seeing whether calculating a combined indirect and total effect consisting of each of the three factors could prove informative. We found that the combined indirect ($\beta = .06$, $p < .001$) and total ($\beta = .28$, $p < .001$) effects of engagement across all three dimensions by way of both affective and cognitive math attitudes were significant. This may indicate a partial mediation in a low-stakes context, considering significant indirect and total effects as well as a significant direct association between engagement and the learning outcome. The interpretation of the combined total effect should be handled cautiously as the effect requires a more complex interpretation, which is another issue addressed further in the Discussion section.

High-stakes Test Context

Using the same set of latent variables as in the previous model, we next entered students' actual AP score as an indicator of statistics proficiency in a high-stakes context into the SEM as the outcome. Unlike the previous model in which mock AP score was a continuous variable, the actual AP was treated as an ordinal variable with values ranging from 1 to 5. The SEM had reasonably good model fit, $\chi^2(df{=}1449) = 4586.244$, $p < .001$, $CFI = .943$, $TLI = .952$, $RMSEA = .102$ (95% CI: .099, .105), $SRMR = .102$. We again note that the χ^2 test was significant and the RMSEA and SRMR are above the recommended thresholds, which are indices that tend to be sensitive to sample size, non-normality (Ainur et al., 2017) and model complexity (Shi et al., 2019). We again found that the modification indices suggested the addition of regression paths predicting academic procrastination but again opted not to pursue model changes for the reasons explained regarding the previous model.

Given that the goodness-of-fit indices were again either near or within the recommended thresholds, we proceeded with model interpretation. In addition, misspecification of the latent factors seemed unlikely given that we again found all standardized factor loadings were significant ($p < .001$). Table 4 presents the standardized estimates and standard errors for each direct and indirect effect.

Table 4. *Standardized regression coefficients and standard errors for direct and indirect paths in the SEM with students' actual AP score as a learning outcome (N = 209).*

Model Parameters	β (*SE*)	95% CI	*p*	
Direct Effects				
Procrastination → Math Attitudes: Affective	–0.13 (0.03)	–0.19, –0.06	<.001	***
Engagement: Affective → Math Attitudes: Affective	0.21 (0.04)	0.14, 0.28	<.001	***
Engagement: Behavioral → Math Attitudes: Affective	–0.03 (0.05)	–0.12, –0.06	0.462	
Engagement: Cognitive → Math Attitudes: Affective	0.14 (0.04)	0.06, 0.22	<.001	***
Procrastination → Math Attitudes: Cognitive	–0.14 (0.03)	–0.21, –0.07,	<.001	***
Engagement: Affective → Math Attitudes: Cognitive	0.32 (0.04)	0.25, 0.39	<.001	***
Engagement: Behavioral → Math Attitudes: Cognitive	–0.11 (0.05)	–0.21, –0.01	0.023	*
Engagement: Cognitive → Math Attitudes: Cognitive	0.04 (0.05)	–0.05, 0.14	0.369	
Procrastination → AP Exam	0.04 (0.06)	–0.09, 0.16	0.547	
Engagement: Affective → AP Exam	0.29 (0.08)	0.14, 0.44	<.001	***
Engagement: Behavioral → AP Exam	0.05 (0.09)	–0.13, 0.23	0.593	
Engagement: Cognitive → AP Exam	–0.01 (0.09)	–0.18, 0.16	0.907	
Math Attitudes: Affective → AP Exam	0.09 (0.05)	–0.01, 0.18	0.064	
Math Attitudes: Cognitive → AP Exam	0.26 (0.05)	0.16, 0.36	<.001	***

Combined Direct Effects				
Engagement (A + B + C) → AP Exam	0.33 (0.06)	0.21, 0.45	<.001	***
Math Attitudes (A + C) → AP Exam	0.35 (0.04)	0.28, 0.42	<.001	***
Latent Covariance Parameters				
Procrastination ↔ Engagement: Affective	–0.19 (0.01)	–0.21, –0.17	<.001	***
Procrastination ↔ Engagement: Behavioral	–0.66 (0.01)	–0.69, –0.64	<.001	***
Procrastination ↔ Engagement: Cognitive	–0.36 (0.01)	–0.39, –0.34	<.001	***
Engagement: Affective ↔ Engagement: Behavioral	0.50 (0.01)	0.47, 0.53	<.001	***
Engagement: Affective ↔ Engagement: Cognitive	0.69 (0.02)	0.66, 0.72	<.001	***
Engagement: Behavioral ↔ Engagement: Cognitive	0.55 (0.02)	0.51, 0.59	<.001	***
Math Attitudes: Affective ↔ Math Attitudes: Cognitive	0.55 (0.01)	0.52, 0.58	<.001	***
Mediation Parameters				
Mediation by way of Math Attitudes: Affective				
Indirect Effects				
Engagement: Affective → Math Attitudes: Affective → AP Exam	0.02 (0.01)	<.001, 0.04	0.072	
Engagement: Behavioral → Math Attitudes: Affective → AP Exam	<.001 (0.01)	–0.01, 0.01	0.497	
Engagement: Cognitive → Math Attitudes: Affective → AP Exam	0.01 (0.01)	<.001, 0.03	0.116	
Procrastination → Math Attitudes: Affective → AP Exam	–0.01 (0.01)	–0.02, <.001	0.096	
Total Effects (Indirect Effect Plus Direct Effect)				
Engagement: Affective → Math Attitudes: Affective → AP Exam	0.31 (0.02)	0.15, 0.47	0.000	***
Engagement: Behavioral → Math Attitudes: Affective → AP Exam	0.05 (0.01)	–0.13, 0.23	0.615	
Engagement: Cognitive → Math Attitudes: Affective → AP Exam	<.001 (0.09)	–0.17, 0.17	0.979	
Procrastination → Math Attitudes: Affective → AP Exam	0.03 (0.06)	–0.10, 0.15	0.670	
Combined Total Indirect Effect of Engagement				
Engagement (A + B + C) → Math Attitudes: Affective → AP Exam	0.03 (0.02)	<.001, 0.06	0.067	
Combined Total Effect of Engagement				
Engagement (A + B + C) → Math Attitudes: Affective → AP Exam	0.36 (0.06)	0.24, 0.48	<.001	***
Mediation by way of Math Attitudes: Cognitive				
Indirect Effects				
Engagement: Affective → Math Attitudes: Cognitive → AP Exam	0.08 (0.02)	0.05, 0.12	<.001	***
Engagement: Behavioral → Math Attitudes: Cognitive → AP Exam	–0.03 (0.01)	–0.06, <.001	0.039	*
Engagement: Cognitive → Math Attitudes: Cognitive → AP Exam	0.01 (0.01)	–0.01, 0.04	0.390	
Procrastination → Math Attitudes: Cognitive → AP Exam	–0.04 (0.01)	–0.06, –0.01	0.001	**
Total Effects (Indirect Effect Plus Direct Effect)				
Engagement: Affective → Math Attitudes: Cognitive → AP Exam	0.38 (0.08)	0.23, 0.53	<.001	***
Engagement: Behavioral → Math Attitudes: Cognitive → AP Exam	0.02 (0.09)	–0.16, 0.20	0.822	
Engagement: Cognitive → Math Attitudes: Cognitive → AP Exam	<.001 (0.09)	–0.17, 0.17	0.998	
Procrastination → Math Attitudes: Cognitive → AP Exam	<.001 (0.06)	–0.12, 0.13	0.973	
Combined Total Indirect Effect of Engagement				
Engagement (A + B + C) → Math Attitudes: Cognitive → AP Exam	0.07 (0.01)	0.04, 0.10	<.001	***
Combined Total Effect of Engagement				
Engagement (A + B + C) → Math Attitudes: Cognitive → AP Exam	0.40 (0.06)	0.27, 0.52	<.001	***
Mediation by way of Math Attitudes (Combined)				
Combined Indirect Effects				
Engagement: Affective → Math Attitudes (A + C) → AP Exam	0.10 (0.01)	0.07, 0.13	<.001	***
Engagement: Behavioral → Math Attitudes (A + C) → AP Exam	–0.03 (0.01)	–0.06, <.001	0.027	*
Engagement: Cognitive → Math Attitudes (A + C) → AP Exam	0.02 (0.01)	<.001, 0.05	0.100	
Procrastination → Math Attitudes (A + C) → AP Exam	–0.05 (0.01)	–0.07, –0.03	<.001	**
Combined Total Effects (Indirect Effect Plus Direct Effect)				
Engagement: Affective → Math Attitudes (A + C) → AP Exam	0.39 (0.08)	0.24, 0.55	<.001	***
Engagement: Behavioral → Math Attitudes (A + C) → AP Exam	0.02 (0.09)	–0.16, 0.20	0.848	
Engagement: Cognitive → Math Attitudes (A + C) → AP Exam	0.01 (0.09)	–0.15, 0.18	0.873	
Procrastination → Math Attitudes (A + C) → AP Exam	–0.01 (0.06)	–0.13, 0.11	0.886	
Combined Total Indirect Effect of Engagement				
Engagement (A + B + C) → Math Attitudes (A + C) → AP Exam	0.10 (0.01)	0.07, 0.12	<.001	***
Combined Total Effect of Engagement				
Engagement (A + B + C) → Math Attitudes (A + C) → AP Exam	0.76 (0.12)	0.52, 1.00	<.001	***

* $p < .05$, ** $p < .01$, *** $p < .001$

When examining the direct effects of academic procrastination and the aspects of engagement as predictors of students' actual AP exam score, an indicator of proficiency in a high-stakes context, many of the same trends uncovered in a low-stakes context again emerged. Given the strong correlation between the mock AP exam score and the actual AP exam score, $r_{polyserial} = .60$, $p < .001$, it may not come as a surprise that many of the same parameters were significant in the two models. Overall, the model accounted for 54.4% of variation in the actual AP exam score, based on the R^2 value ($R^2 = .544$).

Direct associations between engagement-related behaviors and AP exam score. We first examined the direct effects of predictors on the high-stakes learning outcome, AP exam scores (**RQ1b**). The direct effect of affective engagement was significant in a positive direction ($\beta = .29$, $p < .001$), thus suggesting that students who are more affectively engaged also tend to receive a higher score on the AP exam. None of the other engagement factors were directly associated with AP exam scores. A combined total direct effect of the three dimensions of engagement was positive and significant ($\beta = .33$, $p < .001$).

Direct associations between math attitudes and AP exam score. Next, we examined the direct effects of the two dimensions of math attitudes on the AP exam scores (**RQ2b**). There was a significant and positive association between the cognitive dimension of math attitudes and the actual AP exam score ($\beta = .26$, $p < .001$); however, there was no significant association between affective math attitudes and AP exam scores. The combined effect of both dimensions of math attitudes was significant and positive ($\beta = .35$, $p < .001$), thus consistent with past work showing math attitudes are positively associated with math performance in a high-stakes context.

Direct associations between engagement-related behaviors and math attitudes. When considering math attitudes as an outcome as opposed to a predictor, our findings supported trends found in the previous model predicting variation in the mock AP exam score, a low-stakes learning outcome. Affective engagement was significantly and positively associated with both affective (β =.21, $p < .001$) and cognitive ($\beta = .32$, $p < .001$) dimensions of math attitudes. Academic procrastination was negatively associated with both dimensions of math attitudes (affective: $\beta = -.13$, $p < .001$, cognitive: $\beta = -.14$, $p < .001$). In addition, we found that while cognitive engagement was positively associated with affective math attitudes ($\beta = .14$, $p < .001$), it was not associated with cognitive math attitudes. Behavioral engagement, by contrast, was negatively associated with cognitive math attitudes ($\beta = -.11$, $p < .05$) and was not associated with affective math attitudes. This suggests that students who are more behaviorally engaged in completing the tasks expected within the context of the course are less likely to have positive orientations towards learning math as a subject, a finding we return to in the Discussion section.

Indirect associations with AP exam score. We next examined the indirect effects of academic procrastination and the three aspects of engagement on the AP score by way of the two dimensions of math attitudes (**RQ3b**). The affective dimension of math attitudes did not appear to mediate any of the effects of the engagement-related constructs on the learning outcome, as evidenced by a lack of any significant indirect effects (see Table 4). By contrast, there was both a significant indirect ($\beta = .08$, $p < .01$) and total ($\beta = .38$, $p < .01$) effect of the affective dimension of engagement via the cognitive dimension of math attitudes on the learning outcome. Considering the significant direct effect of affective engagement on the AP exam scores, this finding provides evidence of a partial mediation. Though there were significant indirect effects of behavioral engagement ($\beta = -.03$, $p < .01$) and procrastination ($\beta = -.04$, $p < .01$) on the learning outcome by way of cognitive math attitudes were significant, the total effects were not significant.

We next examined the indirect and total effects of the different engagement-related behaviors by combining both affective and cognitive dimensions of math attitudes. We found significant indirect effects of affective ($\beta = .10$, $p < .001$), behavioral engagement ($\beta = -.03$, $p < .05$) and procrastination ($\beta = -.05$, $p < .001$), but not cognitive engagement. The total effect of affective engagement was again found to be statistically significant ($\beta = .39$, $p < .001$), although the total effects for the other engagement factors (including procrastination) were not. These findings again lend further support for a partial mediation of affective engagement on the high-stakes learning outcome by way of overall math attitudes. We also found that the combined indirect ($\beta = .10$, $p < .001$) and total ($\beta = .76$, $p < .001$) effects of engagement by way of both affective and cognitive math attitudes combined were also significant. Considering a significant direct effect, this suggests an overall partial mediation of engagement on learning in a high-stakes context by way of math attitudes.

Discussion

The present study was motivated by a need to better understand associations between academic procrastination, engagement in a statistics course with respect to affective, cognitive, and behavioral aspects, math attitudes, and learning outcomes. Using a SEM approach, we tested for direct and indirect relations between these latent constructs and as predictors of performance on the learning outcomes. The theoretical model tested is novel for several specific reasons. First, the study employs a split-sample approach to validate measures of academic procrastination and math attitudes within a high school sample. Few previous studies have validated measures of these constructs with a high school sample enrolled in AP coursework, let alone with a rigorous, split-sample approach. Second, the study tests for associations between the engagement-related behaviors, such as procrastination and engagement, and math attitudes with respect to learning outcomes measured in both a low- and high-stakes testing context. Given the well-established link between math attitudes and performance, particularly in a high-stakes evaluative contexts (von der Embse et al., 2018), it would be reasonable to expect that the association between math attitudes and performance would be greater in a high-stakes testing context compared with a low-stakes context. Third, the present study is additionally novel because it shows that the effect of engagement-related behaviors can be partially mediated by math attitudes. While past research has framed math attitudes as an outcome of experience, emotions, and cognitions related to math (Meece et al., 1990), or as a predictor of math performance (Hembree, 1990), we opted instead to examine both its affective and cognitive dimensions as intervening variables. In the present investigation, we therefore consider math attitudes as both an outcome of past academic behaviors and a predictor of future performance in measures of proficiency. This perspective can be justified under the expectancy-value theory (Wigfield & Eccles, 2000).

Some past research on math-related learning has positioned math attitudes as a potential mediator, affecting the strength of the association between other factors and learning (Everingham et al., 2017). However, previous studies have largely not considered multiple testing contexts with different stakes associated with performance. We were especially interested in seeing whether there are substantive differences when examining learning outcomes based on scores derived from a low-stakes testing context as well as a high-stakes testing context. Comparing the trends observed in the two models, one reflecting learning outcomes in a low-stakes testing context and the other reflecting trends in a high-stakes testing context, we find several largely consistent trends. In general, direct paths that were significant in one model, were also significant in the other. The only exception to this is the indirect effect of cognitive engagement as well as the combined indirect effect of engagement on learning, which was significant in the model predicting performance in a high-stakes testing context, but not in the model predicting the same factors in a low-stakes testing context. Furthermore, while there was a direct effect of cognitive math attitudes on learning outcomes in the high-stakes context, but not in the low-stakes assessment context.

Contrasting the two models, one with a low-stakes learning outcome and the other with a high-stakes outcome, substantive differences were found with respect to the proportion of variance each model explained in the learning outcomes. In the model predicting proficiency in a low-stakes testing context, 24.1% of variance in a learning outcome was explained, although in the model predicting a learning outcome in a high-stakes context, 54.4% of variance was explained. These findings suggest that the effect of the predictors is more apparent in a high-stakes as opposed to a low-stakes context. This finding is largely consistent with past research examining math performance in high-stakes or otherwise more stressful evaluative contexts (Beilock, 2008). The size of the proportion of variation is a novel finding. Studies which examine engagement-related behaviors and math attitudes in relation to learning outcomes in a low-stakes context only may thus greatly under-report the associations. As such, future research should acknowledge the salience of the testing context as a factor which may influence the interpretation of the findings.

There presently exists a vast amount of literature linking math attitudes with math achievement (Barroso et al., 2020; Namkung et al., 2019). In the present study, we not only found this association was robust in a statistics-learning context, but also remained so even after taking into consideration the direct effects of students' general tendency to procrastinate in an academic context in addition to students' affective, behavioral, and cognitive engagement within the course. The findings from the present study also contribute to a growing body of literature which considers the structure and unique contributions of certain components of engagement and math attitudes in relation to learning (Goldin et al., 2011). The multi-component perspective on engagement specifies that certain domains of self-appraisals (e.g., affective, behavioral, and cognitive components; see Olson & Maio, 2003) may bear unique associations with other constructs. We found evidence of indirect effects of affective engagement via the two dimensions of math attitudes combined as well as direct effects with respect to the learning outcomes in both models. By contrast, there was no significant direct or indirect effect of cognitive engagement on the learning outcomes in either model. Cognitive engagement may not explain as much variation in learning once accounting for the contributions of affective engagement (Goldin et al., 2011). Furthermore, past research may even suggest that such cognitive appraisals are best viewed as better predictors of motivational beliefs, rather than reliable direct predictors of performance (Zimmerman, 2000). Thus, the effect of cognitive engagement on learning outcomes may be relatively weak once accounting for affective engagement. Like cognitive engagement, we did not find a significant association between behavioral engagement and the learning outcomes in either model.

In contrast to both affective and cognitive engagement, behavioral engagement appeared to trend toward a negative (albeit non-significant) association with math attitudes. This may appear counterintuitive, given that we could reasonably expect students who report being more behaviorally engaged (i.e., demonstrating observable and active participation) to be more in control of their learning, and thus perhaps more likely to experience positive attitudes towards math. However, students who may be more inclined to report behaviorally engaging in the course may be more likely to experience a pressure to succeed in learning the subject matter. Students who reported being more behaviorally engaged may also be more inclined to perform because a sense of pressure to succeed, perhaps as a mechanism of coping with the negative attitudes around the subject matter (see Pekrun, 2006). Furthermore, some evidence suggests that the association between math attitudes and performance may be non-linear. For example, some evidence suggests a curvilinear association between certain negative orientations towards math (particularly math anxiety) and math performance, with motivation towards learning math serving as a moderator (Wang et al., 2015). Such findings indicate that among students with high intrinsic motivation, there was a negative association between math anxiety and performance, while for students with low intrinsic motivation, the association was positive. Students with a high intrinsic motivation who feel more negative math attitudes or anxiety may also tend to assume an active approach to learning the subject matter by being more behaviorally engaged (Middleton & Spanias, 1999). This phenomenon, whereby anxiety leads to improved performance up until a certain level is sometimes referred to as the Yerkes-Dodson law (Wang et al., 2015; Yerkes & Dodson, 1908). In addition, the finding is consistent with past literature that links procrastination and negative orientations towards math with math (Choe et al., 2019) and statistics learning (Onwuegbuzie, 2004), suggesting that a disposition towards task avoidance, particularly in evaluative contexts (Ferrari & Tice, 2000), may be an underlying factor. While the direction of the association between math attitudes and achievement in math-related subject areas is not definitively known, there is some speculation that it is dynamic and reciprocal much like the associations between math anxiety and learning (Carey et al., 2016; Namkung et al., 2019).

There was no evidence of a direct association between academic procrastination and the learning outcomes in either model. Engagement within the context of a course appears to be a more proximal correlate of proficiency within the subject area, whereas academic procrastination in a more general context is not. While it has been found that greater self-regulated learning abilities and a motivation to learn statistics content tends to be associated with decreased procrastination (Dunn, 2014), students who are highly motivated to learn a particular subject matter may still demonstrate self-regulated learning, despite a general tendency to procrastinate (Pintrich, 2000). Thus, we may expect that any effect of general academic procrastination on the learning outcomes would be tempered by other factors. We found some evidence of an indirect effect of procrastination on the high-stakes learning outcome by way of the two dimensions of math attitudes combined, though this effect was rather weak.

Implications

The findings in the present study shed light on the complicated associations between engagement-related behaviors, math attitudes, and achievement. These findings have implications for interventions designed to instill more positive attitudes toward math, and thus perhaps as its positive association with performance on math-related learning outcomes, by promoting certain course engagement-related behaviors. Students who are more likely to experience certain negative orientations toward math may also tend to have higher attainment values (Macher et al., 2015) and may therefore be more driven towards engagement in learning math and related subjects. However, those who experience a high degree of negative math attitudes may also be more inclined to act on performance-avoidance goals in social and evaluative contexts (Liew et al., 2014). Therefore, the inconsistent mediation of behavioral engagement on the learning outcome by way of math attitudes may not be entirely counterintuitive. Students who self-report course-related behaviors associated with math achievement may indeed receive higher scores on tests of subject matter proficiency. Such students may also feel more negatively towards the subject matter. For instructors, providing a variety of math and related subject assessments (e.g., low-stakes/high-stakes, formative/summative) to students may help to promote more positive math attitudes associated with better performance, particularly those who experience more negative math attitudes in high-stakes contexts. Providing the option for students to retake an exam in math and related subjects has also been found to be another effective means of promoting mastery and more positive orientations towards math (Juhler et al., 1998). For students, certain interventions that emphasize cognitive control over negative emotional responses to math stimuli may help to dampen any potential effect of less favorable math attitudes on performance on math-related tasks (Lyons & Beilock, 2011; Ramirez et al., 2018).

Students with more negative math attitudes may be more motivated to engage in math learning tasks in low-stakes or non-evaluative situations as such contexts are less likely to activate performance-avoidance goals (Simzar et al., 2015), which are negatively associated with performance (Middleton & Midgley, 1997). Effective study habits and engagement in low-stakes math-learning contexts may promote the effects of positive math attitudes on performance by enhancing the content knowledge and skills necessary to succeed in even highly stressful evaluative contexts.

Previous educational interventions have also utilized the present perspective, which posits math attitudes as a mediator between engagement-related behaviors and achievement, to improve educational outcomes for students (e.g., Everingham et al., 2017). By concentrating on improving students' engagement-related behaviors, such as course engagement, students may gain a sense of subjective control over math learning. Therefore, in the vein of the expectancy-value theory, an engagement-focused intervention could induce positive achievement emotions, thus promoting the potential influence of positive math attitudes.

Limitations

Despite the novelty of the present findings, there are several potential limitations that may influence the generalizability of the current study's findings. Regarding the sample, the study participants are a convenience sample and may reflect attitudes, behaviors, and learning proficiency representative of a specific subset of high school students. AP courses are designed to teach college-level content throughout the duration of an academic year and give students the opportunity to prepare for an exam, producing scores which many colleges and universities will accept as transfer credits equivalent to course credits received on-campus.

Given the advanced nature of the course content, the sample was likely partially self-selecting, consisting of college-bound high school students. We note, however, that eligibility to participate in AP courses may be enforced to varying degrees in different school types (Long et al., 2019), and especially in smaller schools, certain topics may only be offered in AP format. In such contexts, the assumption that students enrolled in AP courses intend to pursue a college degree may not hold.

Furthermore, the sample appeared to comprise students from relatively affluent households based on key indicators including eligibility for free or reduced-priced lunches as well as parental educational attainment. Though such factors may limit the generalizability of the study's findings to a broader population of U.S. high school students, they nevertheless may be indicative of the status of access and enrollment in AP courses (Schneider, 2009). Thus, it would be worth examining whether relations found in this study are replicable with students in mainstream middle and high school level math and statistics courses.

In addition to concerns over generalizability due to the sample, there are reasons to investigate whether the present findings replicate in other high- and low-stakes assessment contexts. Given that the analyses in the present study used a method of estimation (i.e., diagonally-weighted least squares) that has been found to be equally reliable in handling distributions of continuous variable and ordinal variables (DiStefano & Morgan, 2014), it is unlikely that the differences in parameter estimates are due to fundamental differences in the variable type. However, there may still be fundamental differences in the design of the two assessments used in the present study – aside from the context in which they were administered – that could affect the findings.

Similarly, issues of interpretability surround the context and administration of the self-report measures. The present study used a measure of math attitudes in a general context and thus likely assessed the construct as traits as opposed to states. Whether the findings could differ if the measures referenced students' attitudes in specific testing contexts remains a question to be addressed by further research (e.g., Ashcraft, 2002; Dew et al., 1984). Thus, it is unclear whether including a measure of state-specific math attitudes would account for much additional variation in the learning outcomes used in this study after accounting for the more general measure already used.

As with any analysis involving SEM, there is also the lingering possibility of model misspecification. In both SEM analyses, we found that that RMSEA and SRMR were not below the recommended thresholds for these goodness-of-fit indices. Both the CFI and TLI were acceptable based on the recommended thresholds. We note that both RMSEA and SRMR tend to be more sensitive when sample sizes are small while CFI and TLI are not (Taasoobshiraz & Wang, 2016). However, CFI and TLI may still be prone to misspecification error, particularly when models are complex and sample sizes are small (Shi et al., 2019).

Another limitation of the present study stems from the likely presence of an inconsistent mediation. The direction of the direct and indirect effect for behavioral engagement differs from that of the affective and cognitive engagement dimensions, which tends to occur when there is an inconsistent mediation (MacKinnon et al., 2007; MacKinnon et al., 2000). The total combined effect on the learning outcome, which includes all direct and indirect effects of the three dimensions of engagement, is positive and significant. However, the reported size of the effect may be misleading, and perhaps less robust, because it is likely marred by the inconsistency in the size of the parameter estimates. Considering the direction of the effects, there is a possibility that behavioral engagement is serving as a suppressor variable (see Preacher & Hayes, 2008). These findings speak to the importance of teasing apart the contribution of the unique aspects of a complex construct such as course engagement. Without the multidimensional operationalization of engagement used in the present analyses, the estimates here may have been interpreted without knowledge of the potential for an inconsistent mediation and would not have uncovered the specific contribution of affective engagement.

Conclusions

Few studies have examined how students' engagement within the context of AP classes are directly and indirectly associated with end-of-year learning outcomes by way of math attitudes. Prior research has indicated that instructors may aid students in preventing the detrimental effects that academic procrastination and low course engagement have on learning outcomes by encouraging students to be more organized, achieve higher personal standards, and develop self-regulated behaviors to effectively act upon their motivation to learn (Burnam et al., 2014). Our findings extend prior research by suggesting there is an indirect effect of course engagement, particularly affective engagement, on learning outcomes as measured in a high-stakes, but not a low-stakes, context that appears to be partially mediated by students' math attitudes. The implications are that instructors who can promote opportunities for students to become self-directed and motivated to learn math content may help to bolster the influence that positive math attitudes have on learning outcomes. Additional research should consider whether these associations replicate in non-AP math and statistics classes and in contexts where self-report measures are complemented by data gathered through other modalities, including teacher and researcher observation, physiological, or through digital log data in the case of online learning. Further work should continue to examine math attitudes not only as a predictor of math and statistics learning outcomes, but also as an intervening factor that affects the efficacy of engagement-related behaviors in other statistics and STEM learning contexts.

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