Title: Does Goal-setting Mediate the Growth Mindset's Impact on Math Engagement Differently Depending on Instructional Quality?

Word Count: 1958

1. Objectives

The growth mindset is a belief that intelligence can be developed through hard work, good strategies, and help from others (Dweck & Yeager, 2021). An increasing number of studies have been conducted to assess the impact of a growth mindset on mathematics outcomes (Yeager et al., 2019; Blackwell et al., 2007) and its heterogeneity across school contexts (Qin et al., 2021). It is crucial to investigate further the underlying mediation mechanisms and their heterogeneity to deepen researchers' understanding of how a growth mindset may improve mathematics outcomes and how the mechanism may vary across contexts. Such evaluations will provide important opportunities to confirm, refute, and revise guiding theoretical models of growth mindsets. However, despite substantial theorizing, potential mediation mechanisms underlying the growth mindset's impact have been tested mainly in correlational research but rarely under rigorous causal frameworks (Blackwell et al., 2007). Very few attempts have been made to investigate the heterogeneity of the mediation mechanisms.

This study aims to fill this critical gap by conducting a causal moderated mediation analysis to answer the following two research questions:
(1) How does a growth mindset improve math engagement through mastery goals?
(2) How does this causal mediation mechanism vary by students' perception of instructional quality?

2. Theoretical framework

Incremental theorists of intelligence ("growth-mindset holders") believe that their intelligence is malleable, while entity theorists of intelligence ("fixed-mindset holders") believe that it is stable (Dweck & Leggett, 1988). These mindsets foster different meaning systems in the face of challenges and failures, leading to distinct motivation processes and response patterns (Hong et al., 1999). Growth-mindset holders may attribute their setbacks to their lack of effort, while fixed-mindset holders attribute negative performance to their lack of ability (Hong et al., 1999). Such attribution differences based on mindsets would lead to different goal-setting orientations. Mastery goals focus on maximizing learning opportunities, overcoming difficulties, or improving one's level of competence, while performance goals emphasize demonstrating ability compared with others and justifying one's ego publicly (Wolters, 2004). Dweck and Leggett (1988) showed that growth-mindset holders were more likely to set mastery goals, while fixed-mindset holders tended to set performance goals.

The mastery goal can be a critical link between students' growth mindset and behavioral engagement, as Figure 1 shows. Engagement is the level of students' involvement in the classroom (Skinner et al., 2009). A growth mindset was positively associated with mastery goals (Blackwell et al., 2007). Past research revealed that mastery goals predicted behavioral engagement, such as persistence, effort-making, and lower-level procrastination in math (Wolters, 2004; Miller et al., 1993).

Moreover, past correlation studies suggest that teaching quality is a critical development context that enhances the impact of a growth mindset. We focus on students' perceptions of instructional quality rather than teachers' reports. The former was correlated more strongly with classroom engagement than the latter, indicating that students' perceptions reflect and shape their math engagement (Wang et al., 2020). Wang and Eccles (2013) revealed that students' perceptions of instructional quality predicted their motivation, affecting their level of engagement.

In sum, the previous literature suggests that mastery goals may mediate the growth mindset's impact on math engagement, and this mediation mechanism may be enhanced by students' perceptions of instructional quality. We aim to investigate these mediation and moderated mediation effects under a rigorous causal framework.

3. Methods

Definition

We defined the causal effects under the potential outcomes framework (Neyman et al., 1935) based on the Stable Unit Treatment Value Assumption (Rubin, 1980; VanderWeele & Vansteelandt, 2009). In the causal mediation analysis, the potential outcome depends on the mediator and the treatment variables. Thus, it is defined as a function of both the treatment and the potential mediator (e.g., $Y_i(t, M_i(t))$).

We define the *total treatment effect* (TE) for each individual:

$$\delta_{TEi} = Y_i\big(t_1, M_i(t_1)\big) - Y_i\big(t_2, M_i(t_2)\big),$$

where t_1 stands for high growth mindset levels, and t_2 stands for low growth mindset levels.

The *total indirect effect* (TIE) is defined as:

$$\delta_{TIEi} = Y_i\big(t_1, M_i(t_1)\big) - Y_i\big(t_1, M_i(t_2)\big),$$

which represents the effect of a growth mindset on student i's math engagement transmitted only through the growth mindset-induced change in mastery goals. By taking the average of each individual-specific causal effect over all the individuals, we define the population average causal effect as $\delta_{TIE} = E[\delta_{TIEi}]$, which is the key parameter for answering the research question (1).

Averaging each individual-specific causal effect over all students within high instructional quality ($W_i = w_1$) and low instructional quality ($W_i = w_2$), we define the conditional average TIE as $\delta_{TIEw_1} = E[\delta_{TIEi}|W_i = w_1]$ and $\delta_{TIEw_2} = E[\delta_{TIEi}|W_i = w_2]$. The moderated TIE by instructional quality is defined as a difference between the conditional TIE by two given levels of W_i, $\delta_{TIEMOD} =$

$\delta_{TIEw_1} - \delta_{TIEw_2}$, which is the key parameter for answering the research question (2).

Identification

The identification of causal mediation effects assumes (a) no unmeasured pretreatment confounding of the treatment-mediator, treatment-outcome, or mediator-outcome relationships and (b) no unmeasured posttreatment confounding of the mediator-outcome relationships within levels of moderators. We controlled for pretreatment covariates listed in Table 1; however, assumption (a) may be violated if there are unmeasured pretreatment confounders, such as parents' mindset. In addition, there may also be posttreatment confounders, such as students' affective state. A sensitivity analysis is thus necessary.

Estimation

We fitted mediator and outcome models as shown in Figure 2, which account for the treatment-by-mediator interaction and observed pretreatment confounders. We included the treatment-by-mediator interaction in the model because it is a realistic assumption that the growth mindset's impact on math engagement may vary by mastery goal levels. Because students are nested within classrooms, and the interclass correlation coefficient (ICC) is 0.14, we included a random intercept to account for the correlations among students within the same classroom. The Monte Carlo confidence interval method (Qin & Wang, in press) was used to estimate and test causal effects. The estimand of the population average TIE is:

$$\delta_{TIE} = \left(\beta_m^y + \beta_{tm}^y t\right)\beta_t^m(t_1 - t_2).$$

Sensitivity Analysis

We conducted a sensitivity analysis to assess whether results were robust to potential unmeasured pretreatment confounding variables. The idea is to simulate an unmeasured pretreatment confounder from its conditional distribution at a given strength and compare the results before and after adjusting for it in the analysis (Qin & Wang, in press). The analysis results would be sensitive if the signs or significance of the effects can be altered by an unmeasured confounder that is merely weakly associated with the treatment, mediator, and outcome.

We used the R-package *mice* to impute missing values via multiple imputations (van Buuren & Groothuis-Oudshoorn, 2011). For each imputed data set, we used the R-package *moderate.mediation* (Qin & Wang, 2023) to estimate causal effects, assess sensitivity, and visualize results. The reported results were pooled over ten imputed data sets.

4. Data sources

Participants were 1536 adolescents (51% female; 68% White, 28% Black; 48% low income) from 16 public schools located in a metropolitan area of the northeastern U.S. All students across 16 public schools were asked to participate in a multi-year study on student experiences and positive youth development. Three waves of data (Spring and Fall 2017 and Spring 2018) were used for constructing treatment, mediator, and outcome variables, while prior waves (Fall 2016) were used for creating moderators and pretreatment confounders. In Spring 2017, there were 581 sixth-, 574 eighth-, and 381 tenth-graders. School records provided students' prior math performance and demographic information.

Measures

Treatment-Growth Mindset

A growth mindset is a four-item composite of well-validated Implicit Theory of Intelligence scale (Dweck et al., 1995; Blackwell et al., 2007). The reversed items were recorded so that the higher value indicates a stronger growth mindset. We applied the same reordering procedure to other variables. The growth mindset ranges from 1 to 5 (mean: 3.89, SD: 1.02, α=0.92). In our study, the treatment is continuous. Thus, we set high and low growth mindset levels at one standard deviation above and below the mean (t_1 =4.91 vs. t_2 =2.88), respectively, and focus on assessing the impact of a high vs. low growth mindset.

Mediator-Mastery goals

A measure of mastery goals is a three-item composite of a well-validated Mastery Goal Orientation scale in a widely-used Patterns of Adaptive Learning Scales in math (Midgley et al., 2000). It is a continuous variable, ranging from 1 to 5 (mean: 4.10, SD: 0.98, α=0.90).

Outcome-Behavioral engagement

Behavioral engagement is a composite scale of seven items from a well-validated Classroom Behavioral Engagement scale in math (Wang et al., 2016; Fredricks et al., 2016). The math engagement is a continuous variable, ranging from 1 to 5 (mean: 3.86, SD: 0.84, α=0.89).

Moderator-Instructional Quality

Students' perceived instructional quality of math teachers is a fourteen-item composite of a well-validated Instructional Quality scale (Wang et al., 2020). Items were obtained from five instructional quality constructs: Analysis and inquiry, Content understanding, Quality feedback, Positive climate, and Teacher sensitivity. It ranges from 1 to 5 (mean: 3.92, SD: 0.74, α=0.90). We set high and low teaching quality at one standard deviation above and below the mean ($w_1 = 4.66$ vs.

$w_2 = 3.19$).

Covariates

Rich pretreatment confounders were collected. Table 1 lists all variables with their survey items. Table 2 displays the correlation matrix and descriptive statistics.

5. Results

Does a student's growth mindset improve math engagement through mastery goals on average?

δ_{TE} was positive and significant at a 95% confidence level, indicating that the impact of a growth mindset on math engagement was positive (β = 0.13, Effect size = 0.15). δ_{TIE} was significant (β = 0.03, Effect size = 0.04). When all other possible pathways underlying the impact of a growth mindset on mastery goals were held constant at the level under a high growth mindset, the growth mindset-induced increase in mastery goals significantly increased one's math engagement. The proportion mediated was 0.24, suggesting that the effect of a growth mindset on math engagement was partly transmitted through goal setting.

Does this causal mediation mechanism vary by instructional quality?

δ_{TIEMOD} was positive and significant (β = 0.07, Effect size = 0.09). This indicates that students' perceived instructional quality positively and significantly moderated the mediation mechanism. Figure 3 illustrates how the conditional TIE changed with different levels of instructional quality. The mediating role of mastery goals was more salient with higher perceived instructional quality, and this effect only reached statistical significance when instructional quality was above 4.03. As reported above, the effect size of the average TIE was not large. However, the effect size of the conditional TIE became about 0.10 under high perceived instructional quality. These results indicate that higher instructional quality was a prerequisite for a significant mediating role of mastery goals.

Sensitivity Analysis

The above causal conclusions were made based on the identification assumptions (a) and (b). Assuming no posttreatment confounder of the mediator-outcome relationship, we conducted a sensitivity analysis to assess the influence of unmeasured pretreatment confounding (Qin & Wang, 2023). The results showed that the sign and significance of the original analysis results would not be reversed even if there was a strong unmeasured pretreatment confounder, indicating the robustness of the results.

6. Significance of the study

Our study has several implications for a theoretical model of a growth mindset. First, the present study revealed a motivation process in math learning. Students with a growth mindset would interpret challenging math tasks and mistakes as a growing opportunity, leading to positive classroom engagement. Such a positive behavioral impact would occur partly because of growth-mindset-induced mastery goal setting.

Second, our study implies the context *where* the growth mindset improves math engagement. Our study suggests that instructional quality may be the prerequisite for the growth mindset's impact on the motivation process. A growth mindset intervention is not a panacea but functions in a quality classroom environment. Policymakers should continue investing in improving teaching quality and in creating quality classroom environments where teachers can facilitate students' motivated behaviors.

Our study has limitations as the assumption of no posttreatment confounders may be violated. Future research should investigate the influence of posttreatment confounders on the estimation and inference of causal effects.

Figure 1: Causal Diagram

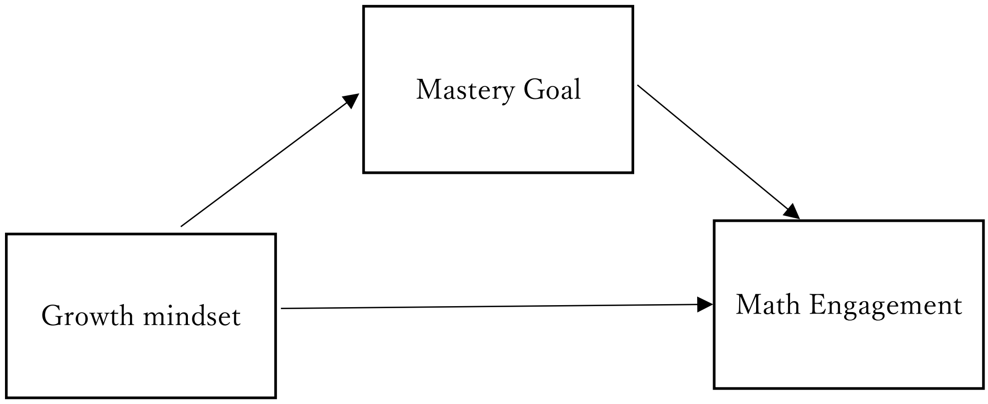


Figure 2: Mediator and outcome models

The mediator model:

$Goal_{ij} = B_0^m + B_t^m Growth_{ij} + \boldsymbol{X_{ij}B_x^m} + r_{ij}^m + u_{0j}^m,$

$r_{ij}^m \sim N(0, \sigma_m^2),$

$u_{oj}^m \sim N(0, \tau_{00}^m),$

The outcome model:

$Engage_{ij} = B_0^y + B_t^y Growth_{ij} + B_m^y Goal_{ij} + B_{tm}^y Growth_{ij} * Goal_{ij} + \boldsymbol{X_{ij}B_x^y} + r_{ij}^y + u_{0j}^y,$

$r_{ij}^y \sim N\left(0, \sigma_y^2\right),$

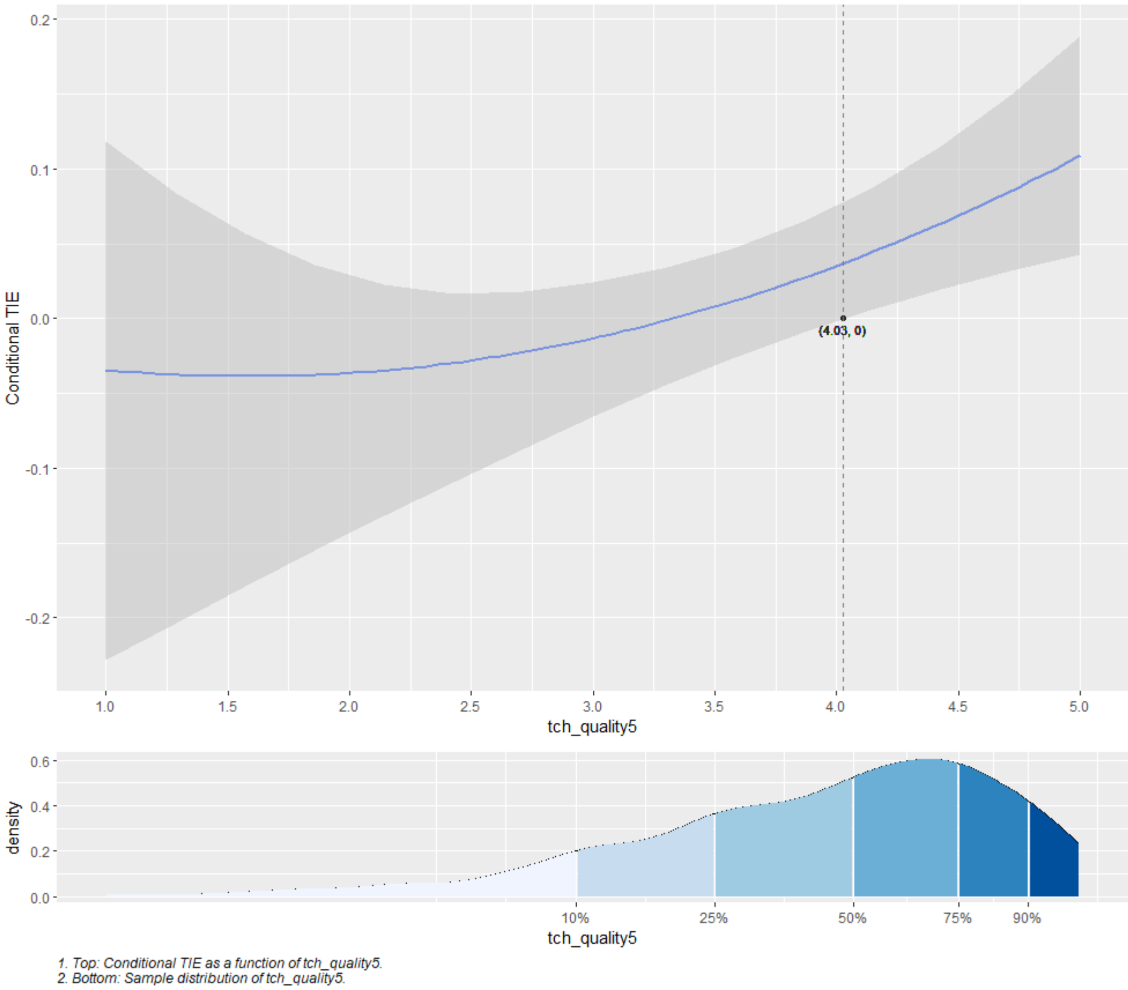
$u_{oj}^y \sim N\left(0, \tau_{00}^y\right),$

where:

$$B_0^m = B_{00}^m + B_{01}^m Instruct_{ij} + B_{02}^m Meta_{ij}$$
$$B_t^m = B_{t0}^m + B_{t1}^m Instruct_{ij} + B_{t2}^m Meta_{ij}$$
$$B_0^y = B_{00}^y + B_{01}^y Instruct_{ij} + B_{02}^y Meta_{ij}$$
$$B_t^y = B_{t0}^y + B_{t1}^y Instruct_{ij} + B_{t2}^y Meta_{ij}$$
$$B_m^y = B_{m0}^y + B_{m1}^y Instruct_{ij} + B_{m2}^y Meta_{ij}$$
$$B_{tm}^y = B_{tm0}^y + B_{tm1}^y Instruct_{ij} + B_{tm2}^y Meta_{ij}$$

Note 1: $\boldsymbol{X_{ij}}$ is a vector of pretreatment confounders for the mediator and outcome model. As Wang et al. (2021) found that metacognition is a significant moderator, metacognition is one of the moderators for a correct specification.

Figure 3: Conditional TIE by instructional quality



Note: The conditional TIE is in effect size. The only dependent variable was standardized. The plot was produced by combining ten imputed data frames.

Table 1: List of variables

Variables	Label
Treatment variable (Spring 2017)	
Growth mindset	To be honest, you can't really change how intelligent you are in math. **(R)**
	You have a certain amount of math intelligence, and you can't really do much to change it. **(R)**
	Your math intelligence is something about you that you can't change very much. **(R)**
	You can learn new things but you can't really change your basic math intelligence. **(R)**
Mediator variable (Fall 2017)	
Mastery goals	One of my goals in math class is to learn as much as I can.
	One of my goals is to master a lot of new math skills this year.
	It's important to me that I improve my math skills this year.
Outcome variable (Spring 2018)	
Behavioral engagement	I stay focused in math class.
	I put effort into learning math.
	I keep trying even if something is hard in math class.
	I complete my math homework on time.
	I don't participate in math class. **(R)**
	I do other things when I am supposed to be paying attention in math class. **(R)**
	If I don't understand a task in math class, I give up right way. **(R)**
Moderator variables (Fall 2016)	
Instructional quality	My math teacher encourages me to solve problems on my own.
	My math teacher asks me to think about what I have learned at the end of activities.
	My math teacher encourages me to consider different solutions and points of view.
	My math teacher explains it in a new way if I say that I don't understand something.
	My math teacher connects what I am learning to what I already know.
	My math teacher provides challenging work in math class.
	My math teacher suggests ways that I can learn more.
	My math teacher keeps working with me until I understand what we are doing.
	My math teacher gives clear instructions for how to do well in math class.
	My math teacher respects me.
	My math teacher says nice things to me.
	My math teacher helps me when I need help.
	I feel comfortable in math class.
	My math teacher understands how I feel about things in class.

Table 1: List of variables (continued)

Meta cognition	I go through the work that I do for math and make sure that it's right.
	I try to connect what I am learning in math to things I have learned before.
	I try to understand my mistakes when I get something wrong in math.
Pretreatment confounders (Fall 2016)	
Male	1: Male, 0: Female
Free/reduced lunch status	1: free/reduced, 0: paid
Special needs status	1: Yes, 0: No
Grade 6 indicator	1: Yes, 0: No
Grade 10 indicator	1: Yes, 0: No
Black	1: Yes, 0: No
White	1: Yes, 0: No
Prior math performance	Math Course Grade (0-100)
Class level	1: Lower Achieving Course, 2: Standard Achieving Course, 3: Higher Achieving Course
Math interest	I look forward to math class.
	I enjoy learning new things about math.
	I feel good when I am in math class.
	I think that math class is boring. **(R)**
Prior Growth mindset	To be honest, you can't really change how intelligent you are in math. **(R)**
	You have a certain amount of math intelligence, and you can't really do much to change it. **(R)**
	Your math intelligence is something about you that you can't change very much. **(R)**
	You can learn new things but you can't really change your basic math intelligence. **(R)**
Prior mastery goals	One of my goals in math class is to learn as much as I can.
	One of my goals is to master a lot of new math skills this year.
	It's important to me that I improve my math skills this year.
Prior Math engagement	I stay focused in math class.
	I put effort into learning math.
	I keep trying even if something is hard in math class.
	I complete my math homework on time
	I don't participate in math class. **(R)**
	I do other things when I am supposed to be paying attention in math class. **(R)**
	If I don't understand a task in math class, I give up right way. **(R)**

Note: **R** indicates the reversed item. Value ranges from 1 to 5 if not specified.

Table 2: Bivariate Correlation Matrix and Descriptive Statistics before imputation

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Growth mindset	**1**																	
2. Mastery goals	**0.21**	**1**																
3. Engagement	**0.22**	**0.48**	**1**															
4. Teaching quality	**0.19**	**0.26**	**0.26**	**1**														
5. Meta cognition	**0.24**	**0.39**	**0.41**	**0.46**	**1**													
6. Male	**-0.06**	**-0.11**	**-0.09**	0.01	**-0.07**	**1**												
7. Free lunch	**-0.09**	-0.05	**-0.20**	**-0.12**	**-0.11**	**-0.01**	**1**											
8. Special needs	**-0.09**	**-0.08**	**-0.08**	**-0.06**	**-0.12**	**0.11**	**0.11**	**1**										
9. Grade 6	**0.10**	**0.18**	**0.15**	0.00	**0.10**	0.02	**0.08**	-0.02	**1**									
10. Grade 10	**-0.10**	**-0.08**	-0.04	**0.07**	-0.04	-0.05	**-0.06**	**-0.06**	**-0.45**	**1**								
11. Black	**-0.06**	-0.02	**-0.14**	**-0.10**	**-0.06**	-0.03	**0.52**	**0.10**	**0.16**	**-0.09**	**1**							
12. White	**0.06**	0.00	**0.12**	**0.09**	0.05	0.04	**-0.52**	**-0.10**	**-0.16**	**0.09**	**-0.91**	**1**						
13. Prior math	**0.22**	**0.25**	**0.38**	**0.25**	**0.28**	**-0.11**	**-0.32**	**-0.16**	**0.07**	-0.03	**-0.30**	**0.29**	**1**					
14. Class level	**0.08**	**0.13**	**0.19**	**0.10**	**0.18**	**-0.07**	**-0.12**	**-0.30**	-0.02	**0.10**	**-0.16**	**0.15**	**0.24**	**1**				
15. Math interest	**0.20**	**0.40**	**0.35**	**0.47**	**0.56**	**0.10**	**-0.06**	-0.02	**0.20**	**-0.13**	0.02	-0.01	**0.27**	**0.07**	**1**			
16. Prior growth mindset	**0.46**	**0.15**	**0.15**	**0.25**	**0.20**	-0.02	**-0.08**	**-0.20**	0.01	**-0.08**	**-0.07**	**0.08**	**0.19**	**0.14**	**0.17**	**1**		
17. Prior mastery goals	**0.22**	**0.46**	**0.36**	**0.48**	**0.56**	0.01	**-0.07**	**-0.09**	**0.15**	**-0.11**	-0.02	0.00	**0.21**	**0.11**	**0.58**	**0.24**	**1**	
18. Prior engagement	**0.23**	**0.40**	**0.52**	**0.44**	**0.63**	-0.03	**-0.22**	**-0.15**	**0.14**	**-0.12**	**-0.19**	**0.18**	**0.42**	**0.19**	**0.60**	**0.25**	**0.59**	**1**
Mean	3.89	4.01	3.86	3.93	3.82	0.49	0.48	0.12	0.38	0.25	0.28	0.68	83.04	2.14	3.32	3.84	4.20	4.16
Standard Deviation	1.02	0.98	0.84	0.74	0.89	0.50	0.50	0.32	0.49	0.43	0.45	0.47	12.38	0.55	1.15	1.10	0.95	0.68
N	1500	1048	1495	1302	1450	1536	1529	1536	1536	1536	1536	1536	1447	1536	1452	1061	1064	1164
% of missingness	2.3%	31.8%	2.7%	15.2%	5.6%	0%	0.5%	0%	0%	0%	0%	0%	5.8%	0%	5.5%	30.9%	30.7%	24.2%

Note: Bolded values indicate significant at $p < .05$.

References

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit Theories of Intelligence Predict Achievement Across an Adolescent Transition: A Longitudinal Study and an Intervention. *Child Development*, *78*(1), 246–263. https://doi.org/10.1111/j.1467-8624.2007.00995.x

Bostwick, K. C. P., Martin, A. J., Collie, R. J., & Durksen, T. L. (2019). Growth orientation predicts gains in middle and high school students' mathematics outcomes over time. *Contemporary Educational Psychology*, *58*, 213–227. https://doi.org/10.1016/j.cedpsych.2019.03.010

Dweck, C. S., Chi-yue Chiu, & Ying-yi Hong. (1995). Implicit Theories and Their Role in Judgments and Reactions: A Word From Two Perspectives. *Psychological Inquiry*, *6*(4), 267. https://doi.org/10.1207/s15327965pli0604_1

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review*, *95*, 256–273. https://doi.org/10.1037/0033-295X.95.2.256

Dweck, C. S., & Yeager, D. (2021). *Global Mindset Initiative Introduction: Envisioning the Future of Growth Mindset Research in Education* (SSRN Scholarly Paper No. 3911564). https://doi.org/10.2139/ssrn.3911564

Fredricks, J. A., Wang, M.-T., Schall Linn, J., Hofkens, T. L., Sung, H., Parr, A., & Allerton, J. (2016). Using qualitative methods to develop a survey measure of math and science engagement. *Learning and Instruction*, *43*, 5–15. https://doi.org/10.1016/j.learninstruc.2016.01.009

Hong, Y. Y., Chiu, C. Y., Dweck, C., Lin, D., & Wan, W. (1999). Implicit Theories, Attributions, and Coping: A Meaning System Approach. *Journal of Personality and Social Psychology*, *77*, 588–599. https://doi.org/10.1037/0022-3514.77.3.588

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., & Urdan, T. (2000). Manual for the patterns of adaptive learning scales. *Ann Arbor: University of Michigan*, 734-763.

Miller, R. B., Behrens, J. T., Greene, B. A., & Newman, D. (1993). Goals and perceived ability: Impact on student valuing, self-regulation, and persistence. *Contemporary Educational Psychology*, *18*(1), 2–14. https://doi.org/10.1006/ceps.1993.1002

Neyman, J., Iwaszkiewicz, K., & Kolodziejczyk, St. (1935). Statistical Problems in Agricultural Experimentation. *Supplement to the Journal of the Royal Statistical Society*, *2*(2), 107–180. https://doi.org/10.2307/2983637

Qin, X. & Wang, L. (2023). Package 'moderate.mediation'. R package version 0.0.5. https://cran.r-project.org/web/packages/moderate.mediation/index.html

Qin, X. & Wang, L. (in press). Causal Moderated Mediation Analysis: Methods and Software. Behavior Research Methods.

Qin, X., Wormington, S., Guzman-Alvarez, A., & Wang, M.-T. (2021). Why Does a Growth Mindset Intervention Impact Achievement Differently across Secondary Schools? Unpacking the Causal Mediation Mechanism from a National Multisite Randomized Experiment. *Journal of Research on Educational Effectiveness*, *14*(3), 617–644. https://doi.org/10.1080/19345747.2021.1894520

Rubin, D. B. (1980). Randomization Analysis of Experimental Data: The Fisher Randomization Test Comment. *Journal of the American Statistical Association*, *75*(371), 591–593. https://doi.org/10.2307/2287653

Skinner, E. A., Kindermann, T. A., & Furrer, C. J. (2009). A motivational perspective on engagement and disaffection: Conceptualization and assessment of children's behavioral and emotional participation in academic activities in the classroom. *Educational and Psychological Measurement*, *69*(3), 493–525. https://doi.org/10.1177/0013164408323233

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Vanderweele, T. J., & Vansteelandt, S. (2009). Conceptual issues concerning mediation, interventions and composition. *Statistics and Its Interface*, *2*(4), 457–468. https://doi.org/10.4310/SII.2009.v2.n4.a7

Wang, M.-T. & Eccles, J. S. (2011). Adolescent Behavioral, Emotional, and Cognitive Engagement Trajectories in School and Their Differential Relations to Educational Success, *Journal of Research on Adolescence*, 22 (1), 31-39. https://onlinelibrary-wiley-com.pitt.idm.oclc.org/doi/10.1111/j.1532-7795.2011.00753.x

Wang, M.-T., Fredricks, J. A., Ye, F., Hofkens, T. L., & Linn, J. S. (2016). The Math and Science Engagement Scales: Scale development, validation, and psychometric properties. *Learning and Instruction*, *43*, 16–26. https://doi.org/10.1016/j.learninstruc.2016.01.008

Wang, M.-T., Hofkens, T., & Ye, F. (2020). Classroom Quality and Adolescent Student Engagement and Performance in Mathematics: A Multi-Method and Multi-Informant Approach. *Journal of Youth and Adolescence*, *49*(10), 1987–2002. https://doi.org/10.1007/s10964-020-01195-0

Wang, M.-T., Zepeda, C. D., Qin, X., Del Toro, J., & Binning, K. R. (2021). More Than Growth Mindset: Individual and Interactive Links Among Socioeconomically Disadvantaged Adolescents' Ability Mindsets, Metacognitive Skills, and Math Engagement. *Child Development*, *92*(5), e957–e976. https://doi.org/10.1111/cdev.13560

Wolters, C. A. (2004). Advancing Achievement Goal Theory: Using Goal Structures and Goal Orientations to Predict Students' Motivation, Cognition, and Achievement. *Journal of Educational Psychology*, *96*(2), 236–250. https://doi.org/10.1037/0022-0663.96.2.236

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., Harn, P.R., Gopalan, M., Mhatre, P., Ferguson, R., Duckworth, A.L., & Dweck, C. S. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, *573*(7774), Article 7774. https://doi.org/10.1038/s41586-019-1466-y