Predicting engineering student success: An examination of college entrance exams, high school GPA, perceived competence, engineering achievement, and persistence

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WIP: Predicting engineering success: An examination of college entrance exams, high school GPA, self-efficacy, achievement, and persistence

This Work in Progress paper seeks to better understand whether changes in academic self-efficacy explain the relations of prior achievement (i.e., high school GPA and entrance exams) to future achievement and persistence of engineering students. College entrance exams, such as the ACT and SAT, and high school GPA (HSGPA) are traditionally used for college admission decisions, because both are believed to predict achievement. While HSGPA tends to be a consistent predictor of achievement, prior studies show conflicting results as to whether college entrance exams predict academic achievement in engineering, especially beyond students' first year of college [1-7]. Additional work suggests that HSGPA and college entrance exams predict persistence in the first semester of college, but there is limited research examining how prior achievement relates to persistence towards degree completion [8]. Due to these mixed results, it is critical to understand not only *whether* students' HSGPA and entrance exam scores both predict college achievement and persistence, but *why* they are or are not predictive. Furthermore, as universities use both criteria (HSGPA and entrance exam scores) for admission decisions [9], it is important to understand if they are equally predictive of success. As colleges seek to foster students' achievement and persistence, it is also important to understand how prior achievement influences later achievement (e.g., the underlying psychological mechanisms), so that targeted support can be provided [3,10,11].

One potential psychological mechanism that may underpin this past-future achievement relation is academic self-efficacy (e.g., beliefs about one's ability to learn and do work in a particular academic domain [14]). Past literature has commonly examined the relations between past and future achievement, but less work has addressed the psychological mechanisms that may explain *why* these relations are observed. Social cognitive theory suggests that students' competence beliefs are shaped by prior evaluative experiences [12], which may influence their sense of competence throughout college, and in turn their academic engagement and achievement. According to the model of triadic reciprocal causation stipulated by social cognitive theory, self-efficacy is developed through prior success and is an important predictor of future achievement [13]. According to this model, one makes sense of one's ability to complete a task (i.e., self-efficacy) based on one's prior experiences, which influence subsequent behaviors (i.e., persistence) and future achievement [15]. Examining self-efficacy as a potential psychological mechanism may improve our understanding of how and why achievement in high school influences achievement and persistence in engineering studies, in college, and beyond [16]. The present study builds upon our initial findings [17] to examine how engineering students' self-efficacy changes across all four years of college, as this may relate to the "leaky pipeline" phenomenon in engineering/STEM [17].

Current Study

The present study used a latent growth curve model to investigate how engineering students' academic self-efficacy changed over four years of college as a function of entrance exams (math

ACT and math SAT) and HSGPA, and how changes in self-efficacy related to persistence and achievement-associated outcomes. Math ACT scores were used rather than composite ACT scores because prior math achievement is an important indicator of engineering outcomes [18]. Our internal (unpublished) assessments have also shown that math ACT score is the most reliable predictor of student persistence among the standard admissions criteria. Specifically, we addressed the following research questions:

(1) How are college entrance exam scores and HSGPA related to achievement (i.e., GPA), persistence in engineering, and engineering career intentions at the end of college?
(2) Are the relations of college entrance exam scores and HSGPA to achievement, persistence, and career intentions explained by initial levels and changes in engineering students' self-efficacy?

Aligned with social cognitive theory [9], we hypothesized that prior achievement would inform students' self-efficacy beliefs, resulting in a positive relation to both the initial levels and changes in academic self-efficacy. Moreover, we expected that the association between prior achievement and self-efficacy would help explain how and why prior achievement predicts later achievement and persistence in engineering.

Method

Participants: The present study used longitudinal data from a large, public, midwestern university. Participants were 1,472 students who, at any time, participated in an annual survey of engineering students. The survey was conducted in the Spring of 2016 (T1), 2017 (T2), 2018 (T3), and 2019 (T4). Of the respondents, 321 (25.5%) identified as female. The majority of students identified as White (64.3%), while the remaining students identified as African American (7.5%), Latinx (4.8%), Asian (20.9%), Multiracial (2.2%), Alaska Native (0.2%), and Native Hawaiian or Other-Pacific Islander (0.1%). The surveyed students included both students enrolled in engineering majors and students who, at one point, were engineering majors but were no longer enrolled in engineering.

Measures:

Academic Self-efficacy. Five questions measured engineering self-efficacy [19]. The responses were recorded using a 5-point Likert-type scale. These measures were collected annually over four years (T1 $\alpha = .87$, T2 $\alpha = .90$, T3 $\alpha =.91$, and T4 $\alpha =.90$). A sample item for engineering self-efficacy is "*I'm certain I can master the content in the engineering-related courses I am taking this semester.*"

Prior Achievement. Prior achievement was measured using students' HSGPA and math ACT scores. Students' HSGPA and highest math ACT (or converted math SAT using act.org concordance table) score was obtained from institutional records.

Persistence. Student persistence was assessed using institutional data for the students' enrolled major in their third or fourth year. Persistence was measured as a categorical variable (1 = engineering majors, 0 = non-engineering majors).

Career intentions. To measure engineering career intentions, students were prompted with the following question each year: *"To what extent do you intend to pursue a career in engineering?"* and responded on a 10-point scale, with one being *"I definitely will not"* and ten being *"I definitely will."* Students' fourth-year engineering career intentions were used in this study.

College Achievement. Institutional data for students' last reported or final, undergraduate, cumulative GPA.

<u>Results</u>

Preliminary Analyses. Descriptive statistics, correlations, and missing data analyses were conducted (Table 1). These analyses showed that math ACT scores were associated with students' self-efficacy at times T2-T4, persistence, and career intentions (Table 1, column 2). Additionally, students' academic self-efficacy beliefs were significantly associated with each other across time and students' persistence and career intentions were significantly related to prior achievement and self-efficacy. Finally, an examination of the means for self-efficacy suggests that students' academic self-efficacy decreased between T2 and T3 (Table 1, means of columns 3-6).

Growth Model. Longitudinal measurement invariance and latent growth curve analysis were tested using Mplus v.8.4 [20], based on full information maximum likelihood (FIML) to account for missing data [21,22]. Model fit was evaluated using the Comparative Fit Index (CFI; values $\geq$ .90 for adequate fit; values $\geq$ .95 for excellent fit, [23]) and root mean square error of approximation (RMSEA; values < .08 for acceptable fit). Prior to conducting growth models, we conducted longitudinal confirmatory factor analysis on academic self-efficacy to test for measurement invariance across time. These analyses were conducted to confirm that observed changes were not due to changes in the perceived meaning of the construct over time [24, 25]. Strict invariance was achieved and applied to all further modeling. An unconditional model of self-efficacy suggested linear change, χ^2 (211) = 602.368; RMSEA = 0.04; CFI = 0.95, TLI = 0.96. This linear model suggested that academic self-efficacy begins higher in students' first year (i_{mean}= 3.80) and declines between freshman and senior year (b = -.05, p < .001). A linear model was determined to represent the data sufficiently and was used to examine the relation of change in self-efficacy with predictors and outcomes.

A conditional, linear growth model was fit to examine the relation of math ACT scores and HSGPA to initial levels and growth (e.g., change) in academic self-efficacy during four years of college, and, in turn, how prior achievement and academic self-efficacy related to cumulative GPA, major persistence, and engineering career intentions, assessed during the fourth year of college (see Figure 1 for the conceptual model). The model fit the data well: χ^2 (301) = 604.173; RMSEA = 0.03; CFI = 0.94, TLI = 0.94. As presented in the upper portion of Table 2, math ACT was related to initial level of academic self-efficacy (b = .02, p = .02), while HSGPA was unrelated. Both math ACT and HSGPA were positively related to changes in academic self-efficacy (math ACT slope: b = 0.01, p = .02; HSGPA slope: b = .09, p = .02). Specifically, students who entered college with higher math ACT scores and HSGPAs experienced smaller declines in their academic self-efficacy throughout college. In terms of outcomes, the slope of academic self-efficacy was positively related to persistence in an engineering major ($b = 3.26$, $p < .001$), engineering career intentions ($b = 6.83$, $p < .001$), and college GPA ($b = 1.91$, $p < .001$). This suggests that having smaller declines in self-efficacy was positively related to fourth-year engineering persistence and college achievement. The intercept of self-efficacy was related to major persistence ($b = .49$, $p = .005$) and engineering career intentions ($b = 1.91$, $p < .001$), but unrelated to college GPA.

We also examined the direct effects of prior achievement to the indicators of persistence and achievement. We found that HSGPA was related to major persistence (slope: $b = .56$, $p = .004$) and college GPA (slope: $b = .59$, $p < .001$) but did not find a direct relation with career intentions. Moreover, math ACT scores were related to major persistence (slope: $b = .05$, $p = .001$) and college GPA (slope: $b = .02$, $p = .045$) but were unrelated to career intentions.

For indirect effects of math ACT to the indicators of persistence through initial levels (intercept) and change (slope) in self-efficacy, there was a statistically significant indirect effect of slope ($b = 0.02$, $p = .04$) on college GPA and engineering career intentions ($b = .05$, $p = .04$), and indirect effect of intercept on engineering major persistence ($b = 0.03$, $p = .04$). Furthermore, there was a statistically significant indirect effect of slope of academic self-efficacy between HSGPA and engineering major persistence ($b = 0.31$, $p = .049$) and career intentions ($b = .64$, $p = .045$). No significant indirect effects were found for HSGPA and college GPA mediated by academic self-efficacy. Indirect effects are displayed in Figure 2.

Discussion

In the present study, we examined the relations among prior achievement, initial levels and growth in academic self-efficacy, and persistence-related outcomes for undergraduate engineering students. Latent growth curve analyses suggested that students with higher math ACT scores and higher HSGPAs had lower declines in academic self-efficacy across four years of college. This extends our prior work that found engineering students' math ACT scores were related to changes in academic self-efficacy in their first two years of college [17].

Our analyses showed that math ACT scores and HSGPA directly predicted changes in self-efficacy and further predicted persistence in engineering and cumulative college GPA; however, neither predicted engineering career intentions. Additionally, math ACT scores predicted initial levels of self-efficacy but HSGPA did not. These results support social cognitive theory and our hypotheses, as it suggests that students' perceptions of evaluative feedback are an underlying mechanism to explain the relation of prior and later achievement [13]. Our findings also suggest that the type of evaluative feedback (i.e., HSGPAs, which vary by school, or standardized test scores, which are normed on a national scale) may differentially influence students' initial competence beliefs [15]. One reason that math ACT is a stronger predictor than HSGPA of initial academic self-efficacy could be due to the specificity of the evaluative measure. HSGPA, which reflects performance in all subject areas over time, is likely not as informative for students' initial evaluation of their ability to be successful in engineering as math ACT scores, given the emphasis on math in engineering coursework [26, 27]. Additionally, as students move toward larger academic settings, they may use normative measures like standardized test scores to make initial self-comparisons to inform their self-efficacy [14].

These findings support the notion that academic self-efficacy may be one mechanism that explains the relation of prior achievement with persistence and achievement in engineering, as change in self-efficacy was associated with continued enrollment in an engineering major, engineering career intentions, and cumulative college GPA. Evidence from this study suggests that the relations of HSGPA and math ACT scores with students' initial self-efficacy and engineering outcomes may be different, which supports the hypothesis that students' competence beliefs are domain-specific [26, 27]. Therefore, a practical implication of this study is that engineering programs should seek to provide students' with early experiences in introductory engineering courses and early start math courses, specifically to foster their sense of self-efficacy (i.e., mastery experiences, vicarious experiences, social persuasions, and positive physiological states), and in turn, their persistence and achievement in engineering [28]. Thus, an avenue for future research would be to examine how specific sources of self-efficacy influence changes in engineering students' self-efficacy across college.

Tables and Figures

Table 1. *Descriptive Statistics of Study Variables*

	1	2	3	4	5	6	7	8	9
1. HS GPA	--								
2. Math ACT	$.43^{**}$	--							
3. Acd. Self-Eff (T1)	-.04	.03	--						
4. Acd. Self-Eff (T2)	.07	$.16^{**}$	$.47^{***}$	--					
5. Acd. Self-Eff (T3)	$.14^{**}$	$.20^{**}$	$.41^{**}$	$.63^{**}$	--				
6. Acd. Self-Eff (T4)	$.11^{*}$	$.14^{**}$	$.41^{**}$	$.50^{**}$	$.65^{**}$	--			
7. Persistence	$.32^{**}$	$.31^{**}$	$.14^{**}$	$.24^{**}$	$.37^{**}$	$.39^{**}$	--		
8. College GPA	$.50^{**}$	$.36^{**}$	.05	$.18^{**}$	$.27^{**}$	$.33^{**}$	$.50^{**}$	--	
9. Career Intentions	$.11^{**}$	$.14^{**}$	$.26^{**}$	$.28^{**}$	$.42^{**}$	$.48^{**}$	$.65^{**}$	$.19^{**}$	--
N	1207	1360	827	670	703	6102	1472	1467	603
M	3.72	27.91	3.80	3.80	3.66	3.68	0.58	3.06	7.41
SD	0.36	4.32	0.67	0.75	0.85	0.82	0.49	0.71	2.99

Observed correlations, means, and standard deviations were calculated in SPSS. Acd. Self-Eff (T1) = Academic Self-Efficacy at time 1, (T2) = time 2, (T3) = time 3, and (T4) = 4, College GPA = cumulative GPA. ($^{**}p < .01$, $^{*}p < .05$)

Table 2. *Direct Effect Parameters for Conditional Latent Growth Models*

Model and Predictors	Intercept		Slope		Cum. GPA		Persistence		Career Int.	
	b	β	*b*	β	*b*	β	*b*	β	*b*	β
HS GPA	-.12	-.09	$.09^{*}$	$.19^{*}$	$.60^{***}$	$.32^{***}$	$.58^{**}$	$.18^{**}$	.25	.03
Math ACT	$.02^{**}$	$.16^{**}$	$.01^{*}$	$.19^{*}$	$.02^{*}$	$.10^{*}$	$.05^{***}$	$.20^{***}$	.01	.01
Intercept	--	--	--	--	.02	.01	$.49^{**}$	$.21^{*}$	1.91^{***}	$.30^{***}$
Slope	--	--	--	--	1.91^{***}	$.50^{***}$	3.26^{***}	$.49^{***}$	6.83^{***}	$.39^{***}$

HSGPA = high school GPA, Cum. GPA = Cumulative GPA, Career Int. = Career intentions. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

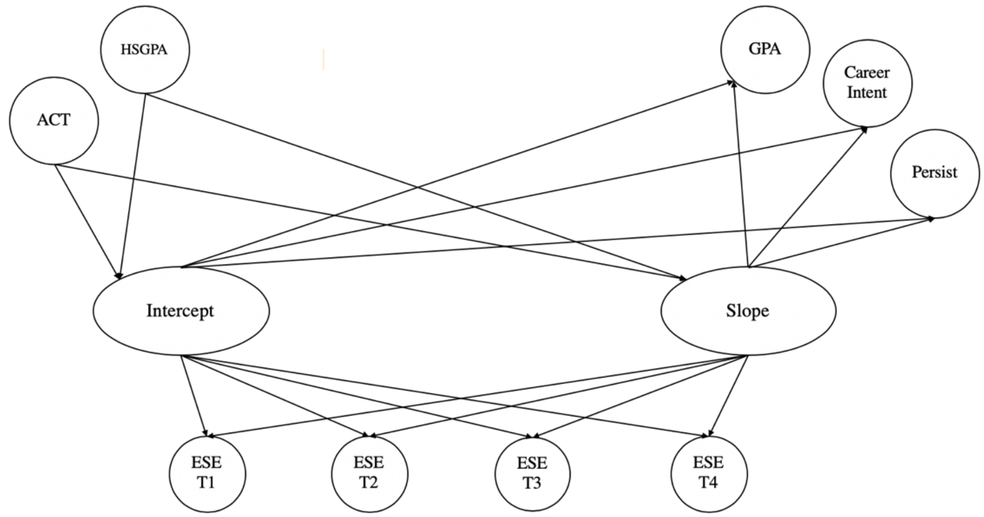

Figure 1. Conceptual path model. ACT = Math ACT; HSGPA = high school GPA; ESE = engineering/academic self-efficacy; Career Intent = engineering career intentions; Persist = persistence in engineering major. Direct relations from predictors to outcomes are not depicted in the path model but were tested.

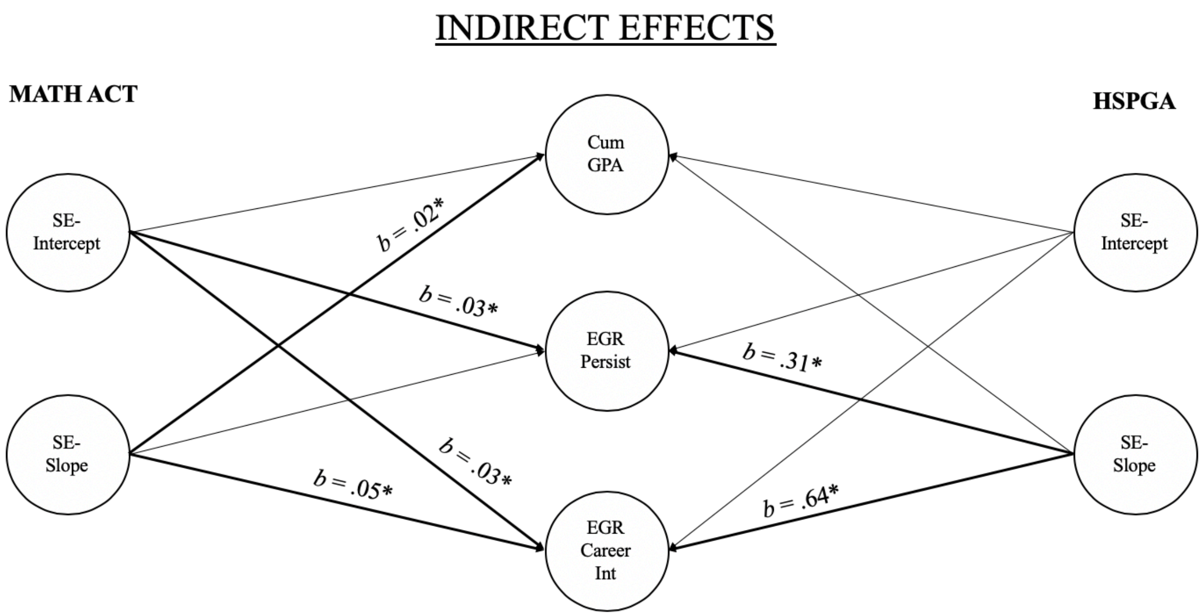

Figure 2. Indirect effects of math ACT and HSGPA, through self-efficacy (SE), to Cum GPA = cumulative college GPA, EGR Persist = persistence in an engineering major, and EGR Career Int. = engineering career intentions. Bolded paths are significant. ***p < .001, **p < .01, *p < .05

References

[1] S. Katz, G. J. Lautenschlager, A. B. Blackburn, and F. H. Harris, “Answering Reading Comprehension Items without Passages on the SAT,” *Psychol. Sci.*, vol. 1, no. 2, pp. 122–127, Mar. 1990.

[2] R. Zwick and J. Greif Green, “New Perspectives on the Correlation of SAT Scores, High School Grades, and Socioeconomic Factors,” *J. Educ. Meas.*, vol. 44, no. 1, pp. 23–45, Mar. 2007.

[3] T. Abdel-Salam, P. Kauffmann, and K. Williamson, “A case study: DO high school GPA/ SAT scores predict the performance of freshmen engineering students?,” *Proc. - Front. Educ. Conf. FIE*, vol. 2005, pp. 7–11, 2005.

[4] B. F. French, J. C. Immekus, and W. Oakes, “A structural model of engineering students success and persistence,” *Proc. - Front. Educ. Conf. FIE*, vol. 1, p. T2A19-T2A24, 2003.

[5] S. D. Brown, S. Tramayne, D. Hoxha, K. Telander, X. Fan, and R. W. Lent, “Social cognitive predictors of college students’ academic performance and persistence: A meta-analytic path analysis,” *J. Vocat. Behav.*, vol. 72, no. 3, pp. 298–308, 2008.

[6] J. C. F. De Winter and D. Dodou, “Predicting academic performance in engineering using high school exam scores,” *Int. J. Eng. Educ.*, vol. 27, no. 6, pp. 1343–1351, 2011.

[7] Brenda Hannon, “Predicting College Success: The Relative Contributions of Five Social/Personality Factors, Five Cognitive/Learning Factors, and SAT Scores,” *J Educ Train Stud.*, no. 1, pp. 1–7, 2015.

[8] S. Stewart, D. H. Lim, and J. Kim, “Factors Influencing College Persistence for First-Time Students,” *J. Dev. Educ.*, vol. 38, no. 3, pp. 12–20, 2015.

[9] F. L. Oswald, N. Schmitt, B. H. Kim, L. J. Ramsay, and M. A. Gillespie, “Developing a Biodata Measure and Situational Judgment Inventory as Predictors of College Student Performance,” *J. Appl. Psychol.*, vol. 89, no. 2, pp. 187–207, 2004.

[10] C. J. Fong, T. W. Acee, and C. E. Weinstein, “A Person-Centered Investigation of Achievement Motivation Goals and Correlates of Community College Student Achievement and Persistence,” *J. Coll. Student Retent. Res. Theory Pract.*, vol. 20, no. 3, pp. 369–387, 2016.

[11] O. Eris *et al.*, “Outcomes of a Longitudinal Administration of the Persistence in Engineering Survey,” *J. Eng. Educ.*, pp. 371–395, 2010.

[12] J. E. Jacobs, S. Lanza, D. W. Osgood, J. S. Eccles, and A. Wigfield, “Changes in Children’s Self-Competence and Values: Gender and Domain Differences across Grades One through Twelve,” *Child Dev.*, vol. 73, no. 2, pp. 509–527, Mar. 2002.

[13] F. Pajares and D. Shunk, *Self-beliefs and school success: Self-efficacy, self-concept, and school achievement*. London: Ablex Publishing, 2001.

[14] M. Bong and E. M. Skaalvik, “Academic Self-Concept and Self-Efficacy: How Different Are They Really?,” *Educ. Psychol. Rev.*, vol. 14, no. 1, 2003.

[15] D. Schunk and B. J. Zimmerman, “Influencing Children’s Self-Efficacy and Self-Regulation of Reading and Writing Through Modeling Dale,” *Read. Writ. Q.*, vol. 23, no. 1, pp. 7–25, 2007.

[16] National Academies of Sciences, Engineering, and Medicine, “Supporting students’ college success: Assessment of intrapersonal and interpersonal competencies. Board on

Testing and Assessment, Division of Behavioral and Social Sciences and Education.," 2016.

[17] K. A. Robinson *et al.*, "Motivation in Transition: Development and Roles of Expectancy, Task Values, and Costs in Early College Engineering," *J. Educ. Psychol.*, vol. 111, no. 6, pp. 1081–1102, 2018.

[18] C. P. Benbow, "Identifying and nurturing future innovators in science, technology, engineering, and mathematics: A review of findings from the study of mathematically precocious youth," Peabody J. Educ., vol. 87, pp. 16–25, 2012.

[19] N. A. Mamaril, E. L. Usher, C. R. Li, D. R. Economy, and M. S. Kennedy, "Measuring Undergraduate Students' Engineering Self-Efficacy: A Validation Study," J. Eng. Educ., vol. 105, no. 2, pp. 366–395, Apr. 2016.

[20] L. K. Muthén and B. O. Muthén, Mplus, Statistical Analysis with Latent Variables, Eighth. Los Angeles. [20] C. K. Enders and J. L. Peugh, "Using an EM covariance matrix to estimate structural equation models with missing data: Choosing an adjusted sample size to improve the accuracy of inferences," *Structural Equation Modeling*, vol. 11, no. 1. pp. 1–19, 2004.

[21] C. K. Enders and J. L. Peugh, "Using an EM covariance matrix to estimate structural equation models with missing data: Choosing an adjusted sample size to improve the accuracy of inferences," Structural Equation Modeling, vol. 11, no. 1. pp. 1–19, 2004.

[22] C. K. Enders, *Applied Missing Data Analysis*. New York London: The Guilford Press, 2010.

[23] L. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model. A Multidiscip. J.*, vol. 6, no. 1, pp. 1–55, Jan. 1999.

[24] W. Meredith, "Measurement Invariance, Factor Analysis, and Factorial Invariance," *Psychometrika*, vol. 58, no. 4, pp. 525–543, 1993.

[25] R. J. Vandenberg and C. E. Lance, "A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research," *Organ. Res. Methods2*, vol. 3, no. 1, pp. 4–70, 2000.

[26] R. Scherer, "Further Evidence on the structural relationship between academic self-concept and self-efficacy: On the effects of domain specificty," *Learn. Individ. Differ.*, vol. 28, pp. 9–19, 2013.

[27] U. Trautwien, O. Lüdtke, I. Schnyder, and A. Niggli, "Predicting homework effort: Support for a smoain-specifc, multilevel homework model," *J. Educ. Psychol.*, vol. 98, no. 2, pp. 438–456, 2006.

[28] E. L. Usher and F. Pajares, "Soruces of self-efficacy in mathematics: A validation study," *Contemp. Educ. Psychol.*, vol. 34, pp. 89–101, 2009.