# UNDERREPRESENTED STUDENTS' MOTIVATIONAL ATTITUDES IN MATHEMATICS

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It is widely agreed that attitudes about mathematics play an important role in students' performance, choice, and persistence in STEM. Motivational theories posit this link and suggest that differences in these attitudes should explain in part why female, Black, Hispanic, low-income, and first-generation students are underrepresented in STEM fields in the United States. This study employed nationally representative data from the High School Longitudinal Study of 2009 (HSLS:09) and structural equation modeling to study five types of math attitudes: self-efficacy, identity, interest, utility, and cost. Multi-group factor analytic methods were used to compare mean levels of these attitudes across subgroups based on STEM career expectations, college generational status, parent income, gender, and race. The results suggest that explaining underrepresentation in STEM via differences in motivational attitudes is not straightforward.

Keywords: Affect, Emotion, Beliefs, and Attitudes; Equity, Inclusion, and Diversity.

Broadening participation in science, technology, engineering, and mathematics (STEM) has become a critical effort across the globe to further innovation and strengthen economies (Freeman et al., 2015). Internationally, female students and students from socioeconomically disadvantaged backgrounds are less likely to aspire to STEM careers (OECD, 2016). In the United States, where gender, class, and race are interconnected (Shields, 2008), STEM degree earners are disproportionately White or Asian males, especially in engineering and the physical, computer, and mathematical sciences (NSF & NCSES, 2021). Moreover, the Black/African American, Hispanic/Latinx, and Indigenous students who do attain STEM degrees and occupations disproportionally leave the STEM workforce (Riegle-Crumb et al., 2019). Underrepresentation is a critical issue as not only do workers in STEM occupations earn more, but workers with STEM degrees earn higher wages, regardless of whether they work in STEM occupations (Noonan, 2017). Furthermore, compared to other occupations, STEM jobs offer the smallest pay gaps across gender and racial/ethnic lines (Carnevale et al., 2011). Therefore, broadening participation in STEM is of critical importance not only as a means to help meet demand for STEM-competent workers, but also for addressing social and economic inequalities. Several factors contributing to the underrepresentation of certain groups in STEM have been studied. Some of the most common include academic performance, opportunity to learn, and motivational attitudes, which all tend to be closely linked (OECD, 2016). This study focuses on attitudes towards mathematics and how they differ across well-represented and underrepresented groups with the following research questions: Are there differences in students' attitudes about mathematics across gender, race, and social class backgrounds? If so, do these differences explain underrepresentation in STEM, i.e., do students belonging to the groups with disproportionate representation in STEM have less positive math attitudes on average compared to well-represented groups in STEM?

## **Theoretical Framework**

The framework that this study uses to understand students' mathematics attitudes is expectancy-value (EV) theory (Eccles, 2009). EV theory holds that students' choice, performance, and persistence in achievement-related tasks are most proximately determined by their expectation

for success and their subjective value of the tasks. Expectancy attitudes include self-efficacy or confidence to successfully perform the tasks involved. Value attitudes include identity or belonging within the tasks' domain, interest or enjoyment of the tasks, utility or usefulness of the tasks for future goals, and the perceived cost (e.g., social, time, effort) associated with engaging in the tasks. Applying the theory to STEM, students with higher mathematics and science expectancies and values are more motivated to participate and achieve in STEM. The research literature has largely corroborated the EV model. Indeed, studies have associated more positive mathematics and science EV attitudes with higher achievement in mathematics (Sharpe and Marsh, 2021; Simpkins et al., 2006), higher levels of mathematics and science coursework (Froiland and Davison, 2016; Guo et al., 2015; Simpkins et al., 2006; M.-T. Wang, 2012; X. Wang, 2013), greater interest in STEM careers (Andersen and Ward, 2014; Gottlieb, 2018; M.-T. Wang, 2012; X. Wang, 2013), a higher likelihood of enrolling in a STEM degree program (Federman, 2007; Guo et al., 2015; Trusty, 2002), a higher likelihood of attaining a STEM degree (Ma, 2011; Maltese & Tai, 2011), and a higher likelihood of being employed in a STEM occupation (Eccles and Wang, 2016; M.-T. Wang et al., 2015).

The EV model also explains that due to societal, cultural, and educational influences, EV attitudes differ across gender, race, and social class background. Groups that develop less positive attitudes about mathematics and science because of these influences are less motivated in STEM and hence less likely to participate and achieve in STEM. Studies in Canada, Australia, and the United States have attributed lower female participation in STEM to less positive attitudes about mathematics (Guo et al., 2015; M.-T. Wang et al., 2015; Watt et al., 2012). However, in terms of race/ethnicity, this explanation remains an open question (Andersen and Ward, 2014; Gottlieb, 2018; Riegle-Crumb & King, 2010). This is because much of the EV research has been limited to White, middle-class populations, but this study aims to address this gap with nationally representative data.

### Methodology

## **Data Source and Sample**

To answer the research questions this study employed data from the first wave of the High School Longitudinal Study of 2009 (HSLS:09), a study that follows a nationally representative sample of U.S. students from high school to postsecondary years. Compared to previous studies administered by the National Center for Education Statistics (NCES) it has a unique focus on pathways into STEM. The first wave of data collection began in the fall of 2009 with a sample of over 23,000 ninth graders (typically 14 to 15 years old) attending 944 public and private schools throughout the United States. Sampling involved a complex, two-stage design in which eligible schools were randomly selected first, stratified by school type (public, private) and region, and then students within those schools were randomly selected, stratified by student race/ethnicity. Relatively small groups were oversampled. Participating students completed a mathematics assessment and a questionnaire about their high school experiences and attitudes, including their attitudes towards mathematics (Ingels et al., 2011).

The sample in this research consisted of a subset of the full HSLS:09 sample who identified as Asian, Black or African American, Hispanic or Latino/a, or White. For the feasibility of multigroup analysis, it was chosen to focus on these groups. The 2,300 students identifying as Native American, Alaska Native, Native Hawaiian, or belonging to two or more races were not included in the analysis, leaving a total of 21,180 cases. After proper weighting procedures (see below), the analytic sample is representative of all U.S. students who were ninth graders in 2009 and identified as belonging to one of the above racial/ethnic groups.

### Measures

Six scales represented student's ninth-grade EV attitudes towards mathematics. The scales were measured via confirmatory factor analysis using various base-year survey items. Higher scores on these scales indicate a greater sense of expectancy or value and hence a more positive attitude towards mathematics. The questionnaire wordings for cost pertained to both mathematics and science disciplines. To facilitate interpretation across the attitudes, cost items were reverse coded so that higher scores on this scale also represent a more positive attitude (i.e., a less costly view). All items were measured on four-point Likert scales. Table 1 presents the survey items used to measure these scales, along with Cronbach's alpha ( $\alpha$ ) measures of internal consistency.

To examine differences, several grouping variables were used. The high math achievement group consisted of students scoring in the top quintile of the algebraic reasoning assessment. STEM career expectation was represented by a binary variable indicating that the students' expected occupation at age 30 was in a STEM field. STEM occupations included careers in life and physical sciences, engineering, mathematics and information technology. Low income indicated the students' family income was below 185 percent of the federal poverty threshold. First-generation indicated that neither parent had a four-year degree. To analyze differences across gender and race/ethnicity, an intersectional approach was used (Shields, 2008). Students were grouped into eight mutually exclusive categories: Asian female, Asian male, Black or African American female, Black or African American male, Hispanic or Latina female, Hispanic or Latino male, White female, and White male. To facilitate comparison against the dominant group in STEM, White male was used as the reference group (Riegle-Crumb & King, 2010).

Factor (Cro	onbach's Alpha)
Promp	•
Ite	
Self-Efficacy (	
How n math c	nuch do you agree or disagree with the following statements about your Fall 2009
	You are confident that you can do an excellent job on tests in this course.
	You are certain that you can understand the textbook in this course.
	You are certain that you can master the skills being taught in this course.
4.	You are confident that you can do an excellent job on assignments in this course.
Identity ( $\alpha = .8$	(4)
	do you agree or disagree with the following statements?
	You see yourself as a math person.
2.	Others see you as a math person.
Interest ( $\alpha = .7$	8)
How n course	nuch do you agree or disagree with the following statements about Fall 2009 math
	You are enjoying this class very much.
2.	You think this class is a waste of your time. (Reverse coded)
3.	You think this class is boring. (Reverse coded)
Utility ( $\alpha = .78$	
	nuch do you agree or disagree with the following statements about your Fall 2009
	ourse? What students learn in this course
	is useful for everyday life. is useful for college.
	is useful for a future career.
<b>T</b> ' <b>O</b> (	
Time Cost (α =	81) nuch do you agree or disagree with the following statements? If you spend a lot of
	and effort in your math and science classes
	you won't have enough time for hanging out with your friends. (Reverse coded)
2.	you won't have enough time for extracurricular activities. (Reverse coded)
Social Cost (a	= .83)
	nuch do you agree or disagree with the following statements? If you spend a lot of
	nd effort in your math and science classes
	you won't be popular. (Reverse coded)
2.	people will make fun of you. (Reverse coded)

**Table 1: Factor Items for Math Attitude Scales** 

SPSS 24 was used to clean the data, perform descriptive statistics, and estimate alpha reliabilities. Mplus 8.7 was then used to perform several confirmatory factor analyses (CFAs). A single group CFA was performed on the whole sample, then four multi-group CFAs were performed across subsamples based on (a) STEM career expectation, (b) family income, (c)

college generational status, and (d) race/ethnicity and gender. The CFAs assessed the convergent and discriminant validity of the measurement model (the model specifying the factor structure) and assessed model fit. Assessing convergent and discriminant validity involves examining factor loadings, which indicate the degree to which items are related to each other, and factor correlations. Items measuring one construct should load highly on that factor and not highly on others. Also, for a factor to be distinct it should not be highly correlated with others. Assessing model fit involves examining fit indices (Dash & Paul, 2021). Cutoff criteria for these values are outlined in the next paragraph.

In Mplus, the MLR estimator (Muthén & Muthén, 2017) was used which is robust against nonnormality and accounts for MAR (missing at random) missing data via full information maximum likelihood estimation (FIML; Peugh & Enders, 2004). Balanced repeated replication (BRR) weighting procedures (Asparouhov & Muthén, 2010) were employed to handle the complex sampling design of HSLS:09 (students within schools). The HSLS:09 survey weight W1STUDENT was used in combination with its corresponding 200 BRR weights (see Ingels et al., 2014). Model fit was assessed with the standardized root mean square residual (SRMR) index, which was the only index available when using BRR weighting (Asparouhov & Muthén, 2018). SRMR values less than .05 and .08 are considered excellent and acceptable fits, respectively (Dash & Paul, 2021; Hu & Bentler, 1999). Convergent validity was assessed by examining standardized factor loadings. Loadings of .6 or higher are considered signs of good convergent validity (Dash & Paul, 2021). Discriminant validity was assessed by examining factor correlations. Correlations above .85 are considered high and signs of a lack of discriminant validity (Awang, 2014).

The next step was to examine differences across groups. Standardized latent mean difference tests were conducted which hold the mean of the reference group to zero and estimate the number of standard deviations the other group means are above or below zero. Statistical significance of the differences is then assessed via t-tests (Byrne, 2011). Therefore, the values on the attitude scales reported in the results do not represent absolute attitude levels, but rather attitude levels relative to the reference group.

#### **Results**

The CFA began by testing the validity of the measurement models. With the original items from HSLS:09, the self-efficacy, identity, and utility scales had all their standardized factor loadings well above the .6 cutoff. The interest and cost scales though required some adjusting. Only 3 of the original 6 items that HSLS:09 created to measure interest were retained. The favorite and least favorite school subject items and the item about whether the student was taking their math course because they enjoy math had standardized factor loadings below the .4 and were removed. Although the item about thinking the class is a waste of time had a factor loading below .6, at .58 it was between .4 and .6 so it was retained (Awang, 2014). When all grouped together, the four cost items showed weak intercorrelation. However, it was found that there was high correlation in two pairs-one with the items relating to the social cost of engaging in math and science and the other relating to time and effort. Their standardized factor loadings were above the .6 cutoff, so the two measures were considered distinct constructs. The factor loadings were also checked across each subsample in the multigroup models. All standardized factor loadings were above the .6 threshold (except for the one interest item which was between .4 and .6). Thus, the revised measurement model met acceptable criteria for convergent validity across all CFA models. Lastly, the factor correlations were examined; none exceeded the .85 threshold indicating that the revised measurement model had good discriminant validity as well.

Next, latent mean difference tests were used to examine differences across groups. Results are standardized and represent the number of standard deviations the group's mean is above (or below) its reference group's mean. Table 2 displays the results for math attitudes across the educational and family background groups. The SRMR indices for each multigroup model were around .03 indicating excellent fits. Almost all math attitudes were significantly higher among high math achievers and those expecting to pursue STEM careers. The one exception was that math utility was not found to differ across achievement groups, suggesting that a difference between high math achievers and those expecting to pursue STEM careers is a perceived usefulness of mathematics. Utility perceptions stood out again when comparing attitudes across income and college generational status. Self-efficacy, identity, and time cost were significantly lower on average for low-income students (compared to middle or upper-income students) and lower on average for first-generation students (compared to students who have at least one parent with a college degree). On the other hand, utility was higher for low-income and first-generation students. Interest and social cost had small and less significant differences. In other words, while low-income and firstgeneration students tended to feel less confident in math, less likely to identify as a math person, and found the time commitment for putting effort into math and science to be more costly, they reported more positive perceptions about the usefulness of math and were less likely to be concerned about the social cost of putting effort into math and science.

	High Math Achievement	STEM Career Expectation	Low Income	First-Generation				
Self-Efficacy	.663***	.315***	110**	225***				
Identity	.935***	.436***	109**	194***				
Interest	.392***	.257***	.031	078*				
Utility	025	.406***	.254***	.110**				
Time Cost	.251***	.186***	123*	143***				
Social Cost	.198***	.109*	.079*	.089**				

Table 2: Comparison of Math Attitudes for Math Achievement, STEM Career Expectation,					
Family Income, and College Generational Status Groups					

*Note.* Results are standardized and based on latent mean difference tests; the values represent the number of standard deviations the group's mean is above (or below) its reference group's mean. \*p < .05, \*\*p < .01, \*\*\*p < .001

### Table 3: Comparison of Math Attitudes Across Race/Ethnicity and Gender

	Asian		Black		Hispanic		White
	Male	Female	Male	Female	Male	Female	Female
Self-Efficacy	.352***	.065	.049	.012	048	351***	178***
Identity	.583***	.303***	067	028	086	296***	146***
Interest	.545***	.482***	.140*	.277**	.135*	.011	.071*
Utility	.411***	.065	.472***	.432***	.204***	.125	039
Time Cost	107	.035	061	.253***	167**	.073	.238***
Social Cost	163*	.360***	.097	.337***	.071	.248***	.188***

*Note.* Results are standardized and based on latent mean difference tests; the values represent the number of standard deviations the group's mean is above (or below) its reference group's mean. \*p < .05, \*\*p < .01, \*\*\*p < .001

Table 3 displays the results of the latent mean difference tests for racial, ethnic, and gender groups. The SRMR index for this multigroup model was .042 suggesting an excellent fit to the data. The values in the table represent the number of standard deviations above (or below) that group's means is compared to the mean for white males (which is set to zero). Overall, there were several differences in math attitude levels across the gendered racial/ethnic groups. Asian male ninth-graders tended to have high levels of self-efficacy, identity, interest, and utility, but were more concerned with the social cost of math/science than White male ninth-graders. Asian female ninth-graders had higher levels of identity and interest. Black ninth-graders, both males and females, and Hispanic males tended to have higher interest and utility than White male ninthgraders, and similar levels of self-efficacy and identity. In general, female ninth-graders perceived math and science to be less socially costly as White males ninth-graders. In terms of the time cost, Black and White female students reported math and science as less costly, while Hispanic and Asian female ninth-graders were about even with White male ninth-graders. Only Hispanic male ninth-graders were more concerned than White male ninth-graders. In terms of self-efficacy and identity, Hispanic and White ninth-graders were similar, reporting lower levels than their male counterparts.

#### Discussion

This study found that there were differences in students' attitudes about math across gender, race, and social class backgrounds. Furthermore, within underrepresented groups, students were motivated in mathematics in different ways. While some results confirmed commonly found motivational disparities (M.-T. Wang & Degol, 2013), others identified motivational assets. Ninth-graders belonging to the low-income, first-generation, Hispanic female, and White female groups reported lower confidence in their math abilities and were less likely to identify as a "math person" on average. However, ninth-graders belonging to the low-income, first-generation, Black, and Hispanic groups tended to find math equally or in many cases, more useful. In fact, Black ninth graders tended to report just as high or higher math attitudes in all categories. Therefore,

differences in math attitudes, as measured by HSLS:09 and this research, do not do well to explain underrepresentation in STEM.

The EV attitude that stood out across underrepresented and well-represented groups was math utility. Some qualitative studies suggest explanations for this result. Garibay (2015) found that underrepresented students place high value on effecting social change and impacting communities in need. Students in a study by Aschbacher et al. (2010) cited early interest in STEM for using science to help people and those who persisted in STEM were twice as likely to hold this view. A study by Eastman et al. (2017) followed students in an Urban Scholars program. While the program encouraged STEM, 3 of 4 scholars decided not to continue in STEM due to college experiences suggesting STEM to be uninterested in human interactions and needs. Therefore, underrepresented students tend to be highly motivated by the potential usefulness of math and science to benefit people, especially those in need, and these perceptions are closely tied with their interest and persistence in STEM. Another unexpected result was that female ninth graders tended to be less concerned with the social costs of doing well in math and science. This was surprising as female students are often seen as more likely to be turned away by the "nerd-genius" stereotype in STEM (Starr, 2018).

The results of this study caution a focus on motivational deficits surrounding underrepresented students without simultaneously considering motivational assets. A tangible takeaway is that students from underrepresented groups tend to place a high value on the usefulness of mathematics. Students' self-efficacy and identity, especially for underrepresented groups, should continue to be supported, but stakeholders should not lose sight of the ways in which students are already motivated in mathematics. In particular, the findings of this study suggest that STEM teaching and outreach should also prioritize leveraging the usefulness of mathematics to broaden participation in STEM.

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