Linking Early Science and Mathematics Attitudes to Long-Term Science, Technology, Engineering, and Mathematics Career Attainment: Latent Class Analysis With Proximal and Distal Outcomes

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Abstract

There is a need to identify students' early attitudes toward mathematics and science to better support their long-term persistence in science, technology, engineering, and mathematics (STEM) careers. Seventh graders from a nationally representative sample ($N = 2,861$) were classified based on their responses to questions about their attitudes toward mathematics and science using latent class analysis. Four distinct groups of students that differed in terms of their attitudes were identified. There were relationships between attitudinal group membership, demographic characteristics; mathematics and science achievement; and STEM career attainment. Females and underrepresented minorities were more likely to be in the positive attitude group. However, despite these early positive attitudes, females and underrepresented minorities were less likely to be employed in a STEM career some 20 years later. Information about student interests organized in this manner can be used to better target specific interventions to support and encourage persistence in STEM careers.

Keywords: attitudes, STEM, achievement, mathematics, science

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There is a projected need for a workforce to fill STEM-related occupations and a

projected shortage of students who have the interest and adequate preparation to fill these

occupations (Bureau of Labor Statistics, 2011; Langdon, McKittrick, Beede, Khan, & Doms,

2011; National Science Board, 2007, 2010b). To address this projected need and shortage, much

needs to be done to identify and support students' early interest and persistence of STEM

careers.

There is a large body of literature about the importance of precollege factors that

influence students' persistence in STEM careers (Aschbacher, Li, & Roth, 2010; Sax & Harper,

2007; Tai, Qi Liu, Maltese, & Fan, 2006). One strategy for increasing STEM persistence is to

identify and support high-achieving students who have the potential to succeed the rigorous

mathematics and science demands of STEM careers. Benbow (2012), for example, identified

seventh and eighth graders with high achievement in mathematics. After following these early

high-achieving students for several decades, there is evidence that indicates that these students

were more likely to attain a bachelor's and postsecondary STEM-related degree and persist in -

STEM careers. While focusing only on the top 1% of students is one strategy, it will not

necessarily fill the projected need for STEM-related occupations, particularly the diversity in

STEM occupations that can support various levels of educational accomplishments; and the need

to build a STEM workforce that is representative of the population in terms of gender and

ethnicity.

Other strategies to identify and support a more expanded pool of students looks beyond achievement and focuses, instead, on paying attention to the influence of attitudes, interests, and self-efficacy towards mathematics and science (Gardner, 1975; Louis & Mistele, 2012; Osborne, Simon, & Collins, 2003; Schibeci, 1984). The rationale underlying this approach is that more positive attitudes toward mathematics and science can influence interest in STEM careers and students' motivation to achieve in the areas of mathematics and science. Attention to early attitudes toward mathematics and science provides another way to help identify students who might be interested in pursuing a STEM career.

This approach of focusing on factors other than achievement such as attitudes and aspirations might be particularly useful when trying to recruit students who are not typically represented in STEM fields, including females and underrepresented minorities (see for example, National Science Board, 2010a; National Science Foundation, 2011). Research suggests that achievement alone does not fully account for differences in STEM career persistence by gender or ethnicity (Riegle-Crumb, King, Frodsky, & Muller, 2012) and that instructional opportunities and not necessarily academic potential may account for differences in student achievement by gender and ethnicity. Research based on the United States Census Bureau's 2009 Community Survey indicates that women comprise approximately one half of the workforce, but less than 25% are employed in STEM careers (Beede et al., 2011). Additional data from the 2000 Census suggest that this difference in STEM career employment between males and females has persisted for over a decade. These trends persist despite similar reported early interest in STEM careers (National Academy of Sciences, 2011; Russell, & Atwater, 2005; White, Altschuld, & Lee, 2006).

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Identifying Early Attitudes: A Social Cognitive Perspective on Career Development

From a social cognitive perspective, learning occurs through the interaction of internal

personal factors (such as cognitive, affective, and biological); behaviors; and external

environmental factors (Bandura, 1986). This theory of learning can be used to understand and

predict an individual's behavior and has been extended to theories of how people develop

interests and persist in particular careers (social cognitive career theory). Similar to social

cognitive theory, the social cognitive career theory highlights the importance and mutual

influence of self-efficacy (personal beliefs about one's ability to succeed); outcome expectations

(personal beliefs about the outcome of performing particular behaviors); and personal goals

(Betz & Hackett, 2006; Lent, Brown, & Hackett, 1994, 1996). These social cognitive factors help

individuals regulate their own career behavior by influencing career-related attitudes and

interests, choices, and attainment (Lent & Brown, 1996).

Given the mutual influence of these factors, this theory places importance on early

attitudes and interests in activities that have potential career relevance because these early

activities influence future career interests. For example, consider children who experiment with

different types of materials such as paper, fabric, or rubber learn about characteristics of

materials (waterproof, strong, transparent) and build with these different materials with

encouragement from others (parents and other family members, teachers, peers). These types of

supportive experiences reinforce future choices such as a career as a materials science engineer.

Children without this type of supportive experience are less likely to develop interest in these

types of activities and are less likely to pursue careers that involve these types of interests. Social

cognitive career theory posits that children who have experience and feedback related to

particular types of activities are likely to not only improve their skills in these areas but also to form a sense of their efficacy toward these types of activities.

In terms of career development related to STEM careers, students who have experiences related to STEM are likely to develop a positive attitude toward mathematics and science and perceive that they can succeed in these careers that value these types of skills and experiences. There is theoretical support for focusing on student early attitudes toward mathematics and science and how their understanding of how these subjects are relevant to their future career aspirations influence decisions to pursue STEM careers. However, there is less agreement of how to empirically identify students with early interests.

This study builds on existing literature by examining a method to classify student attitudes toward mathematics and science in seventh grade. This study explores differences in student attitudes by gender, ethnicity, and achievement and relates these differences to whether or not these students were employed in a STEM career by their mid-30s. This study uses a methodology that helps make sense of underlying differences in student mathematics and science attitudes and links these early attitudes to STEM career attainment. In doing so, this study contributes to the literature in the following ways: includes longitudinal data of a national sample of seventh graders, includes mathematics and science attitude variables, and includes outcome of STEM career attainment.

Information from this study can be used to help target programs or interventions to particular groups of students. For example, there might be a group of seventh graders who express positive attitudes toward mathematics but not science. Programs could be targeted to encourage interest in science such as field trips to local science-related business settings to learn more about what science-related careers exist or summer programs that provide opportunities for

students to conduct research with undergraduates majoring in science-related fields. Or suppose

there is a group of students that express positive attitudes toward mathematics and science,

programs could be targeted to this group of students to ensure that this interest is supported

throughout high school through frequent, meaningful experiences with science and mathematics.

Early identification of students with different interests in science and mathematics could be the

first step in providing more specific and informed support to increase the number and quality of

students interested in pursuing STEM careers.

Method

Sample

The sample included participants from the Longitudinal Study of American Youth

(LSAY). The LSAY is a national sample of public school students in 1987 who are now in their

late-30s. The LSAY was funded by the National Science Foundation in 1986 to examine the

development of student achievement in middle and high school and the relationship of those

patterns to career choices. The students included in this particular study were from the seventh

grade cohort. The cohort consisted of students from 52 middle schools across the United States

in 1987. Approximately 60 students were randomly selected from each school. The sample was

predominantly White (70%), with approximately equal numbers of females (48%) and males

(52%). The sample included 9% Hispanic, 11% African American, 4% Asian, and 2% Native

American (5% of students did not indicate any race/ethnicity). Thirty-one percent of the students

in the sample had at least one parent who completed college, while the other 69% did not. In

2007, more than 95% of the original sample completed a questionnaire about their educational

and occupational outcomes (Miller, 2010). These same students were surveyed in 2007 about

their career choices (Miller & Kimmel, 2012). This particular study included data from students

who completed an attitudinal questionnaire and mathematics and science achievement tests in

1987 and career attainment in 2007 ($N = 2,861$).

Measures

Mathematics and science attitudes. Ten items related to mathematics and science

attitudes were included (Table 1). These items were selected based on prior literature on social

cognitive career theory to reflect student enjoyment of mathematics and science; and perceived

usefulness and importance of mathematics and science in the future (Lent & Brown, 2006).

In particular, social cognitive career theory indicates that these constructs should be

considered: self-efficacy, outcome expectations, interests, and goals. To measure self-efficacy,

one item was selected: "I enjoy math." There were two items selected to measure outcome

expectations: "Math is useful in everyday problems" and "Math helps a person think logically,"

and two items were selected to measure interests and goals: "It is important to know math to get

a good job" and "I will use math in many ways as an adult."

This study included items about mathematics and science attitudes because most STEM

careers require both mathematics and science knowledge; and research suggests that attitudes are

content specific and that measures should be tailed to the specific domain (Bandura, 1986;

Hackett & Betz, 1981; Lent & Brown, 2006). The items in science are analogous to the items in

mathematics. For example, one item related to mathematics attitudes is: "Math is useful in

everyday problems," and the item related to science attitudes is "Science is useful in everyday

problems." The response options were: strongly agree, agree, not sure, disagree, strongly

disagree. These options were coded so that a higher value (5) indicated stronger agreement or

more positive attitudes, and a lower value (1) indicated less agreement or less positive attitudes.

Mathematics and science achievement. Student mathematics achievement was assessed in the fall of seventh ($M = 50.47$, $SD = 10.20$) and eighth grade ($M = 53.73$, $SD = 11.09$). The scores were calculated using an Item Response Theory model (Lord, 1980), with a scale ranging from 0 to 100. Each test consisted of items from the National Assessment of Educational Progress (NAEP) and was designed to measure basic skills, algebra, geometry, and quantitative literacy. Seventh grade achievement was considered a covariate, and eighth grade achievement was considered a proximal outcome.

Student science achievement was assessed in the fall of eighth grade ($M = 54.05$, $SD = 11.16$). Similar to the mathematics achievement scores, the science scores were calculated using an Item Response Theory model. The scale ranged from 0 to 100 with items also selected from the NAEP around content areas such as biology, physics, and environmental sciences. Eighth grade science achievement was considered a proximal outcome.

STEM career attainment. In the 2007 questionnaire, respondents were asked about the industry of their current occupation. LSAY created a dichotomous variable to indicate whether or not the respondent was currently employed in a STEM occupation (such as engineering) or not. The particular definition of a STEM career used as an outcome variable in this study included the full range of STEM occupations, but excluded social science occupations. Fifteen percent ($n = 275$) of the sample was employed in a STEM or STEM support occupation. STEM career attainment was used as a distal outcome.

Demographics. Students self-reported their gender and ethnicity. There were roughly similar number of males (51%) and females (49%) included. A dichotomous variable of ethnicity was created: White and Asian (not underrepresented minority); and African American, Hispanic/Latino, and Native American (underrepresented minorities). This grouping is included

because underrepresented minority students have lower representation in STEM careers

compared to other students (see for example, Huang, Taddese, & Walter, 2000). This sample

included 77% White and Asian students and 23% underrepresented minority students.

Analysis

Data was analyzed using Latent Class Analysis (LCA), an analytic technique used to

classify groups of individuals into latent classes based on their responses to the set of indicators

(Bartholomew, 1987; Collins & Lanza, 2010; Goodman, 1974; Heinen, 1996; Lazarsfeld &

Henry, 1968; Muthén, 1992, 2001). LCA is an exploratory multivariate analysis—that is, there is

no apriori specification of the number or type of classes that emerge. LCA differs from the more

commonly used factor analysis in that factor analysis clusters items and LCA clusters

individuals.

Traditionally, LCA models are fit in a series of steps. First, a one-class model is fit and

then the number of classes is increased. The fit of each new model that differs by the

specification on one more class is compared to the previous model. With parsimony in mind, a

model with the greater number of classes is selected only if increasing the number of classes

results in conceptually meaningful groupings and provides good statistical fit. In the present

analysis, once the number of classes was decided upon, covariates (gender, race, and previous

math achievement) were included in the model (Author, 2011); and the means of the distal

outcome were estimated for each class using pseudoclass draws. Pseudoclass draws are a

preferred method for comparing the mean of distal outcomes compared to, say a regression,

because this method takes into account the fact that individuals are not assigned with 100%

certainly into each of the latent classes (Clark & Muthén, 2009). The *p*-values from a series of

pairwise Wald tests (e.g., "auxiliary (e)" in M*plus*) were used to test for significant differences in

means across the classes based on the means from the pseudoclass draws (Muthén &

Asparouhov, 2010). There are several outcomes compared. Eighth grade mathematics and

science achievement were considered proximal outcomes because this was measured a year after

the attitudinal data was collected. STEM career attainment was considered a distal outcome

because this was measured 20 years after the attitudinal data was collected. It is hypothesized

that attitudinal group differences are related to both the proximal and distal outcomes.

In this LCA application, several indicators of model fit were used because there is no

single statistical indicator recommended to assess model fit. We used a combination of statistical

indicators and substantive theory to decide on the best fitting model (Author, 2007; Masyn,

2012). The Bayesian Information Criterion (BIC) (Schwartz, 1978), the most commonly used

and trusted fit indices for model comparison was used, where lower values of the BIC indicated

better fit. Along with the BIC, we compared models that differed in the number of classes using

the Lo-Mendell-Rubin (LMR) and the bootstrap likelihood ratio test (BLRT) to evaluate if

adding an additional class significantly improved model fit (for more on these fit indices, see

Author [2007]). The entropy of the final model selected is reported in the text, but not used for

model fit because it describes the overall classification of students into the latent classes. Entropy

ranges between 0 and 1, where 1 is perfect classification; and values approaching 1 indicate clear

delineation of classes (Celeux & Soromenho, 1996).

Results

The results are divided into three sections: (a) identifying the attitudinal profiles (latent

classes), (b) assessing attitudinal group differences with respect to the covariates, and (c)

assessing the attitudinal profiles with respect to proximal and distal outcomes.

Understanding Math and Science Attitude Profiles

As described earlier, a series of LCA models were fit, specifying 1-8 latent classes. For

each model, fit statistics were collected and used to help inform the decision about how many

classes were sufficient to describe the heterogeneity in student attitudes toward math and science

(Table 2). The lowest value of the BIC (33330.37) was for the 6-class model, although there was

not a large change in the BIC after the 4-class model. The significant *p*-value of the LMR

indicated that a 7-class model fit the data well. There was never a nonsignificant *p*-value for the

BLRT, so this did not inform our decision.

Given these results, the 4-class and 5-class solutions were studied for interpretability.

Four of the five classes were consistent across the two models, and the fifth class was a not

easily interrupted class that did not result in any further information gained about the attitudinal

profiles. For the sake of model parsimony and interpretability, the 4-class model was preferred.

Given the statistical support of the 4-class model, and the substantive plausibility of the solution,

this model was selected as the final model. The entropy for this model was .79, an acceptable

value.

The item profile plot presented in Figure 1 is for LCA model with four latent classes.

Along the *x*-axis are the 10 math and science attitude variables, and along the *y*-axis is the

probability of endorsing a given item. These profile plots are used to understand and label the

latent classes that emerged in LCA. All of the attitudinal items are coded so that 1 indicates a

student endorsed the given item. When interpreting and labeling the emergent latent classes, it

was important to consider both the probability of a class endorsing a given attitudinal item, as

well as how items differentiate the classes.

The four classes were labeled: *Positive, Qualified Positive, Indifferent,* and *Dim*. As seen

in Figure 1, the *Positive* group (25%) indicated consistently positive attitudes toward

mathematics and science as evidenced by a high probability of endorsing the mathematics and

science attitudinal items (labeled with diamonds in Figure 1). The *Qualified Positive* (squares in

Figure 1) group (31%) had a high probability of endorsing the positive attitudes toward

mathematics, but had a low probability of endorsing the science items. Their attitudes toward

mathematics were lower than the *Positive* group and higher than the *Indifferent* group (25%).

However, the science attitudes of the group we labeled *Qualified Positive* (circles in the figure)

were lower than the *Indifferent* group. The smallest group (19%) was labeled *Dim*, due to their

consistently less positive attitudes toward mathematics and science ("X" in the figure).

Assessing Attitudinal Group Differences With Respect to Covariates

The latent class variable was regressed on the covariates. Because the latent class variable

is a categorical latent variable, the regression of this variable on the covariate is a multinomial

logistic regression, and instead of interpreting regression coefficients, we interpreted logits. We

selected the *Positive* class, the group of students with positive math and science attitudes, to be

our comparison group; and compared the other three classes with respect to the covariates.

Specifically, we compared the *Positive* class to the three groups with respect to their values on

the covariate. Table 3 presents the logit parameters, standard errors, corresponding *t*-value and

odds ratio for each comparison.

Comparing the students in the *Qualified Positive* class to the *Positive* class, we found

several significant differences. Specifically, compared to the *Positive* class, minority students

were less likely to be in the *Qualified Positive* class (-.48, *p* < .05, OR = 0.62); and female

students are more likely to be in the *Qualified Positive* class (.83, *p* <.05, OR = 2.28). Lastly,

compared to the *Positive* class, students with higher math scores are less likely to be in *Qualified*

Positive class (-.02, $p < .05$, OR = .98), although given the odds ratio was close to 1, this result was not considered a strong one.

Comparing the students in the *Indifferent* class to the *Positive* class, there were no differences in the prevalence of minority students or gender among these two classes. That is, students that were underrepresented minorities (.02, $p > .05$, OR = 1.0) or female (.28, $p > .05$, OR = .32) were equally likely to in the *Positive* and *Indifferent* classes. There was a small effect of prior math achievement when comparing these two classes. Specifically, as math scores increased, students were slightly less likely to be in the *Indifferent* class compared to the *Positive* class (-.06, $p < .05$, OR = .94).

Lastly, comparing *Dim* to *Positive* class there were differences on all three covariates. That is, students that were minority were less likely to be in *Dim* class compared to *Positive* class (-.40, $p < .05$, OR = .67); and female students were more likely to be in *Dim* compared to *Positive* class (.56, $p < .05$, OR = 1.75). Similar to other class results, students with higher math scores were less likely to be in *Dim* class compared to *Positive* class (-.06, $p < .05$, OR = .95), although this was a small effect.

Predicting Proximal Outcomes Based on Attitudinal Grouping

To explore how important math and science attitudes in seventh grade are in predicting academic outcomes in the following school year, we included two variables: eighth grade mathematics and science achievement and allowed the means to vary across the four groups. With respect to eighth grade mathematics, the results indicated that there were significant differences in the mathematics scores in eighth grade across the test scores ($\chi^2(3) = 65.06$, $p < .001$). As reported in Table 4, students in *Positive* class had the highest mathematics performance in eighth grade, which also was significantly higher compared to the other three classes. The next

highest mean eighth-grade mathematics achievement was students in *Qualified Positive* class,

who were significantly lower than students in the *Positive* class. Students in *Indifferent* and *Dim*

classes were significantly lower than *Positive* and *Qualified Positive* class, but were similar to

each other.

The relationship between the four attitude groups and eighth grade science performance

showed a similar pattern to eighth grade mathematics. Results indicated that there was an overall

mean difference in the science scores across the attitude groups ($\chi^2(3) = 38.44$, $p < .001$).

Students in the *Positive* class had the highest science performance (see Table 4), which was

significantly higher than all of the other classes. The next highest class was the *Qualified*

Positive, which was significantly different from the *Indifferent* class, which had the third highest

science mean. The *Indifferent* and *Dim* class were not significantly different from each other in

terms of their science performance in eighth grade.

Predicting Distal Outcome Based on Attitudinal Groupings

STEM career attainment is considered a long-term, distal outcome in that this occurred

over two decades after the seventh grade attitudinal and achievement data was collected. A Wald

test was used to compare all between-class comparisons to see which attitudinal group was most

likely to eventually go into a STEM career. For this distal outcome, we see an interesting result

(Table 4). Students in the *Positive* class were the most likely among the four classes to go on to a

STEM career. Specifically, approximately 13% of these students ended up in a STEM related

career. Students in the *Positive* class were more likely to be in a STEM career compared to the

students in the other three classes. Following are the *Qualified Positive* and *Indifferent* students,

for which approximately 8% of the students in these classes went into a STEM career. And

lastly, only 4% of the students in the *Dim* class, those who have the lowest math and science attitudes, were the least likely to go into a STEM career.

Combining the covariate and distal analysis results provided an interesting story. As expected, students with high math and science attitudes had the highest subsequent math scores and were more likely to eventually successfully pursue a STEM career. The covariate results indicated that minority and female students were more likely to be in this class compared to *Qualified Positive* and *Indifferent* classes, which is unexpected given the underrepresentation of these groups in STEM career. However, looking closer into the *Positive* class, the group of students most likely to go into a STEM career, only 4% of these students were underrepresented minorities and 10% were female. Even though this group of students was more likely to pursue a career in STEM and females and underrepresented minorities were more likely to be in this group compared to the other three groups, females and underrepresented minorities in this group were less likely than males and Whites and Asians to pursue a STEM career.

Discussion

Using latent class analysis, we found that seventh grade underrepresented minority students were not only similar in their attitudes toward mathematics and sciences compared to males and White and Asian students, but they were actually more likely to be in the *Positive* group compared to other students. However, prior research on STEM careers foreshadows how this story ends. Despite this initial early interest in mathematics and science, data from this sample also indicated that even females and underrepresented minority students in the group of students with the most positive early attitudes toward mathematics and science, there were still far fewer females and underrepresented students who actually persisted in a STEM career.

While attitudes toward mathematics and science do not fully capture the interrelated factors that influence students decisions to pursue a STEM career, this is an aspect that is malleable and influenced by factors such as teacher and family support (Archer et al., 2012; Aschbacher et al., 2010; Dewitt et al., 2011; Osborne et al., 2003). Knowing that females and underrepresented minorities opt out of STEM careers at higher rates than males despite these early positive attitudes toward mathematics and science raises issues of when and why these attitudes start to decline. Future research using longitudinal data can help identify at what time point this interest starts to dip and gaps between females/males, underrepresented minorities/White and Asians become more pronounced.

This study did not attempt to explain these gaps in STEM career attainment for females and underrepresented minorities. Instead, this study applied a method to identify early interests in science and mathematics to allow for more targeted interventions that can provide the sort of deep, meaningful engagement with science and mathematics that will encourage more students to pursue careers in these areas. While we do not expect all students in the *Positive* group to persist in STEM careers; we also do not expect none of the students in the *Dim* group to persist in STEM careers either. Rather, this modeling approach provided a way to organize information about student attitudes in a way that helps target support to different types of students. There is great diversity in STEM careers that all require mathematics and science knowledge but span the full range of level of formal educational attainment. For example, a STEM career includes a materials science engineer who synthesizes new nanoscale materials to address challenges in the area of solar power generation and medical laboratory technicians and a clinical laboratory technician who matches blood for transfusions (Solberg, Kimmel, & Miller, 2012). Even if students to not pursue STEM careers, encouraging and supporting more positive attitudes toward

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mathematics and science nurtures the growth of a more informed public that supports,

appreciates, and is energized by STEM innovations.

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Table 1

Descriptives of Mathematics and Science Attitude Items

	N	*M*	*SD*
I enjoy math	2875	3.71	1.18
Math is useful in everyday problems	2819	3.87	1.01
Math helps a person think logically	2160	3.39	0.78
It is important to know math to get a good job	2824	4.05	0.96
I will use math in many ways as an adult	2829	4.04	0.96
I enjoy science	2857	3.55	1.25
Science is useful in everyday problems	2804	3.26	1.09
Science helps a person think logically	2809	3.47	1.04
It is important to know science to get a good job	2828	3.28	1.09
I will use science in many ways as an adult	2859	3.42	1.13

Table 2

Summary of Latent Class Analysis Fit Indices with 1-8 Latent Classes

Classes	LL	Number of parameters	BIC	ABIC	VLMR p-value	BLRT p-value	Entropy
1	-19319.60	10	38719.49	38687.72	--	--	--
2	-17198.43	21	34565.46	34498.74	0.00	0.00	0.80
3	-16782.26	32	33821.44	33719.76	0.00	0.00	0.75
4	-16587.89	43	33521.03	33384.40	0.00	0.00	0.79
5	-16479.34	54	33392.24	33220.66	0.00	0.00	0.73
6	-16404.25	65	33330.37	33123.84	0.00	0.00	0.74
7	-16368.47	76	33347.13	33105.65	0.00	0.00	0.75
8	-16337.31	87	33373.12	33096.69	0.23	0.00	0.72

Table 3

Log Odds Coefficients and Odds Ratio for 4-Class Model With Minority, Status, and Prior Math Achievement as Covariates, Using the Positive Class as the Comparison Groups

	Logit	SE	est/SE	Odds Ratio
Qualified Positive				
Underrepresented minority	-0.48***	0.17	-2.87	0.62
Female	0.83***	0.13	6.43	2.28
Mathematics achievement	-0.02**	0.01	-2.72	0.98
Indifferent				
Underrepresented minority	0.02	0.23	0.10	1.02
Female	0.28	0.15	1.83	1.32
Mathematics achievement	-0.06***	0.01	-5.17	0.94
Dim				
Underrepresented minority	-0.40*	0.18	-2.22	0.67
Female	0.56***	0.13	4.19	1.75
Mathematics achievement	-0.06***	0.01	-5.16	0.95

Note. Comparison group is "Positive."

p < .05. **p* < .01. ***p* < .001.

Table 4

Comparison of Proximal and Distal Outcomes

Attitudinal Classes	Eighth Grade Math	Eighth Grade Science	STEM Career
Positive	56.92 (0.50)$_a$	56.80 (0.50)$_a$	0.13 (0.02)$_a$
Qualified Positive	55.28 (0.41)$_b$	55.46 (0.42)$_b$	0.08 (0.01)$_b$
Indifferent	50.86 (0.52)$_c$	52.05 (0.53)$_c$	0.08 (0.02)$_b$
Dim	51.64 (0.52)$_c$	51.81 (0.55)$_c$	0.04 (0.01)$_c$

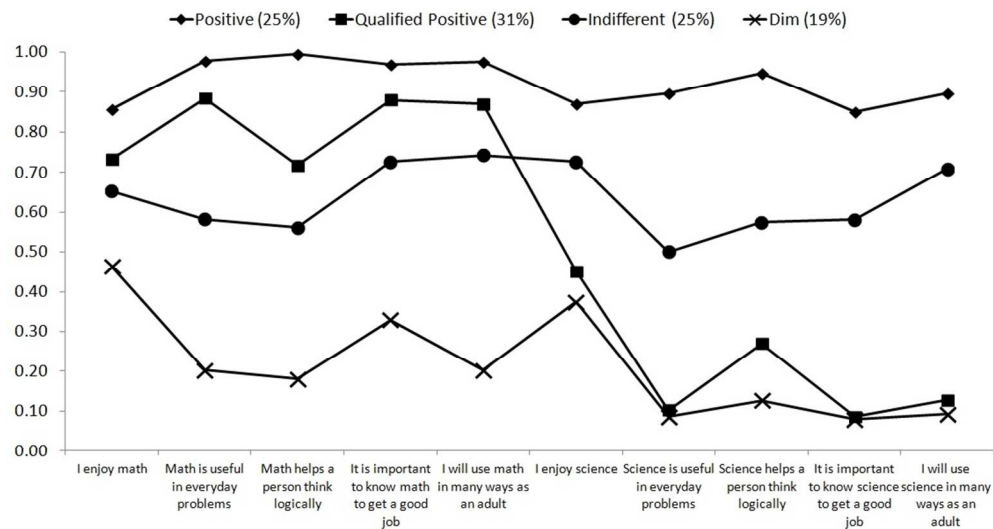*Note.* Means that do not share subscripts differ at $p < .05$.

Figure 1. Item probability profiles.
301x162mm (96 x 96 DPI)