Identifying Early Interest in Mathematics and Science

Abstract

There is a need to identify and support students’ early interest and long-term persistence in science, technology, engineering and mathematics (STEM) careers. Seventh graders from a longitudinal, nationally represent sample (*N* = 3,116) were classified based on their responses to questions about their attitudes towards mathematics and science using latent class analysis. Four distinct groups of students that differed in terms of their attitudes (positive, qualified positive, indifferent, and dim) were identified. There was no relationship between group membership and demographic characteristics (gender, and ethnicity) but there was a consistent, significant relationship between seventh grade mathematics achievement. For example, females were as likely as males as being in the positive attitude group of students. However, despite this initial similarity in seventh grade, females and underrepresented minorities were less likely to be employed in a STEM career. 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 (see for example Bureau of Labor Statistics, 2011; National Science Board, 2007, 2010a; Langdon, McKittrick, Beede, Khan, & Doms, 2011). 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 pre-college factors that influence students’ persistence in STEM careers (see for example, 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 mathematic. After following these early high achieving students for several decades, there is evidence indicates that these students were more likely to attain a bachelors and post-secondary STEM-related degree and persist in a 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 (see for example, Louis & Mistele, 2012). The rationale underlying this approach is that more positive attitudes towards 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 towards mathematics and science provides another way to help identify students who might be interested in pursuing a STEM career.

This approach of focusing 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, females and underrepresented minorities (see for example, National Science Board, 2010b; National Science Foundation, 2004). Research suggests that achievement alone does not fully account for differences in STEM career persistence by gender or ethnicity (Riegle-Crumb et al. 2012) and that differences in instructional opportunities and not necessarily differences in 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 of approximately half of the workforce but less than 25% are employed in STEM careers (Beede, Julian, Khan, Langdon, McKittrick, Khan, & Doms, 2011). Additional data from the 2000 Census suggest that this difference in STEM career employment between males and females have persisted for over a decade. These trends persist despite similar reported early interest in STEM careers (see for example, National Academy of Sciences, 2011; Russell, & Atwater, 2005; White, Altschuld, & Lee, 2006).

**Identifying Early Interests: 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 interests, choices and attainment (Lent & Brown, 1996).

Given the mutual influence of these factors, this theory places importance on early interests in activities with have potential career relevance because these activities will influence future career interests. For example, consider a children who experiment with different types of materials such as paper, fabric or rubber learn about characteristics of 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 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 towards 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-30’s. 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 towards 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**

This sample includes 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 consists of students from 52 middle schools across the United States in 1987. Approximately 60 students were randomly selected from each school. The sample is 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. This study included data from students who completed an attitudinal questionnaire and mathematics achievement test in seventh grade (*N* = 3,116). In 2007, more than 95% of the original sample completed a questionnaire about their educational and occupational outcomes (Miller, 2010).

**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, 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, and interests, 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 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 includes 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) indicates stronger agreement or more positive attitudes and a lower value (1) indicates less agreement or less positive attitudes.

**Mathematics achievement**. Student mathematics achievement was assessed in the fall of seventh grade (*M* = 50.47, *SD* = 10.20). The scores were calculated using an Item Response Theory model (Lord, 1980), with a scale ranging from 0 to 100. There is a mean score of 50 and a standard deviation of 10 for the seventh grade students. Each test consisted of items from the National Assessment of Educational Progress and was designed to measure basic skills, algebra, geometry, and quantitative literacy.

**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 engineering) or not. The particular definition of a STEM career used as an outcome variable in this study includes the full range of STEM occupations but excludes social science occupations. Fifteen percent (*n* = 275) of the sample was employed in a STEM or STEM support occupation.

**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). In 2004, for example, African-Americans made up 12.8% of the population, but only 3.1% of engineers identified as African American in that year. Additionally, Hispanics made up 14.1% of the population in 2004, but only 4.9% of engineers identified as Hispanic in 2004 (National Science Foundation, 2005). This sample includes 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 (Nylund-Gibson & Masyn, 2011) and the means of the distal outcome was 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 five readiness classes based on the means from the pseudoclass draws (seeMuthén & Asparouhov, 2010).

In this LCA application, several indicators of model fit were used since there is no single statistical indicator is recommended to assess model fit. We used a combination of statistical indicators and substantive theory to decide on the best fitting model (Nylund, Asparouhov, & Muthén, 2007). 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 Nylund et al. [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).

Two quasi-Bayesian information-heuristic model fit comparisons, both functions of the individual model BIC values, are also included that have shown promise in latent class growth model selection (Nagin, 1999, 2005) and have been proposed for use with latent class analysis (Masyn, 2012). The Bayes Factor (*BF*) is a pairwise comparison of relative fit between two models. In our study, the computed *BF* approximates the ratio of the probability two models under the assumption that one of the two models being compared is the “true” model. The value of the ratio is then compared to the Jeffery’s Scale of Evident (Wasserman, 2000), for which 1 < *BF* < 3 is considered weak evidence for Model *K* over Model *K +1*, 3 < *BF* < 10 is moderate evidence for Model *K*, and *BF*  > 10 is strong evidence for Model *K*. The other comparison is the approximate correct model probability (*cmP*), which estimates the probability that each model out of a given set of latent class models being considered is correct, under the assumption that the “true” model is contained within that same set of models; thus, the *cmP* values across the given set of models sum to 1.00. The model with the largest *cmP* value is then the model that has the highest probably of being the correct model among the set of models under consideration. See Maysn (2012) for more on these two fit comparisons and their calculations.

**Results**

The results are divided into three sections: (a) identifying the attitudinal profile groups (latent classes), (b) assessing attitudinal group differences with respect to the covariates, and (c) assessing the attitudinal profiles with respect to STEM career attainment.

**Understanding Math and Science Attitude Profiles**

As described before, a series of LCA models were fit specifying 1-6 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 towards math and science (Table 1). The lowest value of the BIC (13223.58), currently the most trusted fit statistic used for LCA models, indicated a 4-class model (Masyn, 2012; Nylund et al., 2007). The significant *p*-value of the LMR indicated that a 2-class model provided superior fit to a 3-class model. There was never a nonsignificant *p*-value for the BLRT, so this did not inform our decision. The Bayes Factor value went from being very small to very large at the 4-class model, and was in the strong fit range for the 4- and 5-class models. Given parsimony, the 4-class model is preferred. Also, the *cmP* value was highest for the 4-class model indicating that this model had the highest probability of being the correct model given the 1-6 class models considered. Given the statistical support of the 4-class model, and the substantive plausibility of the solution, this model was considered the final model. The entropy for this model was .81, an acceptable value.

The four classes were labeled: Positive, Qualified Positive, Indifferent and Dim. As seen in Figure 1, the “Positive” group (25%) indicated consistently positive attitudes towards mathematics and science. The “Qualified Positive” group (31%) expressed positive attitudes towards mathematics but not science. Their attitudes towards mathematic were lower than the “Positive” group and higher than the “Indifferent” group (25%). However, the science attitudes of the “Qualified Positive” group were lower than the “Indifferent” group. The smallest group (19%) was labeled, “Dim” due to their consistently low attitudes towards mathematics and science.

**Attitudinal Group Differences**

Multinomial logistic regression was used to analyze attitudinal group differences (Table 3). Are the numbers in this table right for Gender and Ethnicity? It’s not what I remembered or maybe I’m just not interpreting this right.

**Gender.** Females are more likely to be in the “Qualified Positive” group compared to the “Positive” group. Females are also more likely to be in the “Dim” group compared to the “Positive” group.

**Ethnicity.** Underrepresented minorities are less likely to be in the “Qualified Positive” group compared to the “Positive” group. Underrepresented minorities are less likely to be in the “Dim” group compared to the “Positive” group.

**Mathematics Achievement.** There were consistent differences in group membership related to seventh grade mathematics achievement. Students in the “Qualified Positive”, “Indifferent” and “Dim” group are more likely to have a lower achievement compared to students in the “Positive” group. The coefficients for the three groups are significant and negative which suggests that students with lower achievement are more likely to be in these groups compared to the “Positive” group. This is consistent with research that would suggest that students with higher self efficacy in a particular content area are more likely to enjoy or be more positive toward this content area.

**Relationship to STEM Career Attainment**

There is a significant relationship between the attitudinal profile groups and STEM career attainment. Students with more positive attitudes were more likely to work in a STEM career compared to students with less positive attitudes.

* Percent of female and underrepresented minority students in Class 1

**Discussion (INCOMPLETE)**

In this sample, seventh grade females and underrepresented minority students were not only similar in their attitudes towards mathematics and sciences compared to males and White and Asian students but 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 indicates that females and underrepresented students were less likely to persist in a STEM career.

There might be several reasons for these initial similarities. Students express interest and have high aspirations but XXX (DeWitt, Archer, Osborne, Dillon, Willis, & Wong, 2011)

(Osborne & Collins, 2001)

(Osborne, Simon, & Collins, 2003)

; maybe they don’t know what careers are that use math and science; or maybe they just don’t have the support for this initial interest to sustain them through college. We know that females opt out at higher rates than males and that these differences are most pronounced in college and (as we say with this data) with who actually attains STEM employment. However we don’t know where the breakdown occurs or whether this breakdown is systematic enough to detect and do something about. Future research on this longitudinal data will help identify at what time point this interest starts to dip and gaps between females/males, underrepresented minorities/white and Asians become more pronounced.

There are endless reasons for the gaps in STEM career attainment for females and underrepresented minorities. This study does not attempt to explain these gaps in attainment. Instead, this study applies 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 a STEM careers; we also do not expect none of the students in the “Dim” group to persist in STEM careers either. This modeling approach provides a way to organize student attitudes in a way that helps target support to different types of students to increase the number of students from all groups to persist in a STEM career. There is great diversity in STEM careers –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 towards 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 1-6 Latent Classes*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| *Number of classes* | *Loglikelihood* | *Number of parameters* | *BIC* | *ABIC* | *VLMR* | *BLRT* | *BF* | *cmP* |
| 1 |  |  |  |  |  |  |  | - - - |
| 2 |  |  |  |  |  |  |  |  |
| 3 |  |  |  |  |  |  |  |  |
| 4 |  |  |  |  |  |  |  |  |
| 5 |  |  |  |  |  |  |  |  |
| 6 |  |  |  |  |  |  |  |  |

Table 3

*Summary of Multinomial Logistic Regression*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | *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.



*Figure 1*. Item probability profiles.