Possible Titles:

1. Linking Early Math and Science attitudes to long term career choice: Latent Class Analysis with distal outcomes
2. Using Latent Class Analysis to Analyze Seventh Grade Science and Mathematics Attitudes
3. Similarities in Seventh Grade: Using Latent Class Analysis to Analyze Mathematics and Science Attitudes by Gender and Ethnicity
4. Identifying Early Interest in Mathematics and Science

Abstract

Blah blah blah.

*Keywords*: attitudes, STEM, achievement, mathematics, science

TITLE

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 the early interest and persistence of STEM careers in K-12 settings.

This is an even more acute issue for females and underrepresented minority students (see for example, National Science Board, 2010b; National Science Foundation, 2004). 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.

Research also suggests that underrepresented minority students (such as Black and Hispanic students) are more susceptible to dropping out of STEM careers despite expressing initial interest in STEM careers (Bonous-Hammarth, 2000; Daempfle, 2003; Elliott, Strenta, Adair, Matier, & Scott, 1996; Gándara & Maxwell-Jolly, 1999; National Academy of Sciences, 2011; Grandy, 1998; Oseguera, Hurtado, Denson, Cerna, & Saenz, 2006; Russell, & Atwater, 2005; White, Altschuld, & Lee, 2006). Recent research finds that underrepresented minorities aspire to major in STEM in college at the same rates as their white and Asian American peers but have lower four- and five-year completion rates relative to those of whites and Asian Americans (HERI, 2010, Huang, Taddese, & Walter, 2000). Hurtado, Cabrera, Lin, Arellano, Espinosa (2009) raise the issue that common assumptions regarding racial and ethnic inequality focus on a perceived lack of motivation and preparation within minority populations but that studies have shown many academically well-prepared high school URM students are interested in pursuing scientific and engineering careers (see for example, College Board 2005; Hurtado et al. 2006; NSF 2004).

Add literature about importance of pre-college (k-12) settings (see for example, Sax & Harper, 2007).

So what?

helps to identify and clarify career problems and stimulates constructive discussion of these areas

**Importance of Attitudes in STEM Career Aspirations (1 page)**

Add recent literature (Riegle-Crumb et al., 2012) about lack of achievement differences between males/females; underrepresented minorities/Whites and Asians in K-12 settings. Differences in achievement fail to account for differences in STEM career aspirations.

Add literature about importance of attitudes and aspirations in STEM persistence.

**Mathematics and Science Attitudes (1 page)**

Add literature from science identity from Aschbacher et al. (2010), Archer et al. (2012), Calabrese-Barton et al. (in press)

Add literature from math attitudes and aspirations

This study builds on existing literature about differences in mathematics and science attitudes by examining differences between seventh graders in terms of their mathematics and science attitudes. This study explores whether such differences in attitudes vary 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. In doing so, this study contributes to the existing 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 actual STEM career. Information from this study can be used to help target programs or interventions to particular groups of students. MI: Maybe give hypothetical example of what this means in terms of specific interventions that could raise attitudes for students who are interested in math but not interested in science.

**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 X). These items were selected based on prior literature (see for example, XX, ??). MI: I don’t know if these items were used in another LSAY study? Do you? But if not, we can bring in some theory about why attitudes are important and why these particular items were selected to measure attitudes? Would it make sense to include confirmatory factor analysis results here?

**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 (NAEP, 1986) 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.

LCA models are fit in a series of step, starting with fitting a one-class, unconditional model. Then the number of classes is increased one by one. 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) 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 (2 pages)**

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 presents model fit information for the LCA models with the latent classes that were considered. The lowest value of the BIC (13223.58), currently the most trusted fit statistic used for LCA models, indicated a 5-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 5- and 6-class models. Given parsimony, the 4-class model is preferred. Also, the *cmP* value was highest for the 5-class model indicating that this model had the highest probability of being the correct model given the 1-7-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.

**Understanding the Attitude Profiles**

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 emerge 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 is important to consider both the probability of a class endorsing a given attitudinal item, as well has how items differentiate the classes. The first latent class, denoted by the diamond in Figure 1, was 25% of the sample and was characterized by having a high probability of endorsing all the math and science attitudinal items and as a result, we labeled this class *Name 1*. The latent class denoted by squares in Figure 1, comprised 31% of the sample was characterized by having high math attitude but poor since attitudes, thus we labeled this class Name 2. The latent class denoted by circles was 25% of the sample and had a moderate probability of endorsing all of the math and science attitude items and as a result, we labeled this class *Name 3*. And lastly, the class marked with “X” in Figure 1 was 19% of the sample, had a low probability to endorse all the math and science attitude items so we labeled this class *Name 4*.

**Examining Covariates**

Covariates included in the model, and the latent class variable was regressed on the covariates. Since 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 interpret logits. We have chosen the *Name 1*, the group of students with positive math and science attitudes, to be our comparison group, and we will compare the other three classes with respect to the covariates. Specifically, we compare the *Name 1* class to the three groups with respect to their values on the covariate. Table 3 presents the logit parameters, their standard errors, the corresponding *t*-value, and the odds ratio for each comparison.

Comparing the students in the *Name 2* class to the *Name 1* class, we find several significant differences. Specifically, compared to the Name 1 class, minority students are less likely to be in the Name 2 class (-.48, *p* <.05, OR = 0.62), and female students are more likely to be in the Name 2 class (.83, *p* <.05, OR = 2.28). Lastly, compared to the Name 1 class, students with higher math scores are less likely to be in Name 2 (-.02, *p* <.05, OR = .98), though given the odds ratio close this result is not considered a strong one.

Comparing the students in the *Name 3* class to the *Name 1* class, there are no differences in the prevalence of minority students or gender among these two classes. That is, students that are minority (.02, *p* >.05, OR = 1.0) and female (.28, *p* >.05, OR = .32) are equally likely to in the *Name 1* and *Name 3* classes. There was a small effect of prior math achievement when comparing these two classes. Specifically, as math scores increases, students were slightly less likely to be in the *Name 3* class compared to the *Name 1* class (-.06, *p* <.05, OR = .94).

Lastly, comparing *Name 4* to *Name 1*, class there were covariate differences on all three covariates. That is, students that were minority were less likely to be in *Name 4* compared to Name 1 (-.40, *p* <.05, OR = .67) and females students are more likely to be in *Name 4* compared to Name 1 (.56, *p* <.05, OR = 1.75). Similar to other class results, students with higher math scores were less likely to be in *Name 4* compared to *Name 1* (-.06, *p* <.05, OR = .95), though this was a small effect.

**Predicting STEM Career outcomes based on Attitudinal Groupings in Seventh Grade**

To explore how important math and science attitudes in seventh grade are in predicting later academic and career choices, we included these variables in the analysis. Specifically, we included 8th grade math scores as a proximal outcomes and career choices as a distal outcome and allowed the means to vary across the four latent classes. 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.

With respect to 8th grade math, the results indicated that there were significant differences in the math scores in 8th grade across the test scores (χ2(3)=65.06, *p*<.001). As reported in Table 4, students in *Name 1* had the highest math scores in 8th grade. They were significantly higher than all other classes. The next highest mean scores in 8th grade were students in *Name 2*, who were significantly lower than *Name 1*. The lastly, students in *Name 3* and Name 4 were significantly lower than *Name 1* and *Name 2*, but were similar to each other.

Looking at the long term outcome of STEM career choice (see Table 4), we see an interesting result. Students in the high attitudinal class, *Name 1*, were the most likely among the four classes to go into a stem career. Specifically, approximately 13% of these students ended up in a STEM related career. *Name 1* students were significantly higher in STEM career compared to the other. Following are the *Name 2* and *Name 3* students, for which approximately 8% of the students in these classes went into a stem career. And lastly, students in the *Name 4* class, those who have the lowest math and science attitudes, were the least likely to go into a career, only 4%.

Combining the covariate and distal analysis results provides an interesting story. As expected, students with high math and science attitudes have the highest subsequent math scores and they are the most likely to eventually go into a STEM career. The covariate results indicated that minority and female students were more likely to be in in this class compared to Name 2 and Name 3, which is unexpected given the underrepresentation of these groups in STEM career. Looking closer into the Name 1 class and who among these students were most likely to go into STEM career, we found that of the students that went on to STEM careers, only X% were minority and X% were female.

* Relationship to distal outcome(s). Students with more positive attitudes are more likely to work in STEM. Students with less positive attitudes are less likely to work in STEM.
* Percent of female and underrepresented minority students in Class 1

**Discussion (2 pages)**

In this sample, seventh grade females and underrepresented minority students were not only similar in their attitudes towards mathematics and science compared to males and White and Asian students but, was actually more likely to be in Class 1 compared to other students. However, prior research on STEM career aspirations foreshadows how this story ends. Despite this initial early interest in mathematics and science, females and underrepresented students were less likely to persist in a STEM career.

There might be several reasons for these initial similarities. Flush this out: Students express interest but don’t have interest in an actual career that uses math and science; 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. Identifying this could help target interventions and programs (give concrete examples).

LCA helps us identify who to target support and how to target support. Despite early interest in mathematics and science, X% of the students did not persist in a STEM career. While we would not expect 100% of students to pursue a STEM career, we would hope that this percentage is higher given the diversity and availability of careers that require mathematics and science knowledge.

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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 I 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* |
| Class 2: NAME |  |  |  |  |
| 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 |
| Class 3: NAME |  |  |  |  |
| 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 |
| Class 4: NAME |  |  |  |  |
| 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 “Class 1: NAME”.

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

Table 4.

*Comparison of Proximal and Distal Academic Outcomes Across Additional Classes*

|  |  |  |  |
| --- | --- | --- | --- |
| Attitudinal Classes | 9th Grade Math | STEM Career | Engineer Career |
| Name 1 | 56.92 (0.50)a | 0.13 (0.02)a | 0.4 (0.01)a |
| Name 2 | 55.28(0.41)b | 0.08 (0.01)b | 0.02 (0.01)b |
| Name 3 | 50.86 (0.52)c | 0.08 (0.02)b | 0.02 (0.01)b |
| Name 4 | 51.64 (0.52)c | 0.04 (0.01)c | 0.00 (0.01)c |

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

*Figure 1*. Item probability profiles. MI: I will change names of classes and make this black and white for publication purposes.