Math Motivation Classifications of U.S. High School Students:
What Changes from Grade 9 to Grade 11?

Jason S. Talwar

A thesis submitted in partial fulfillment

of the requirements

for the degree of

Master of Education

University of Washington

2017

Committee:

Elizabeth A. Sanders

Robert D. Abbott

Program Authorized to Offer Degree:

College of Education

Abstract

Understanding motivational classifications around math as a content area for adolescent students is a good first step toward facilitating interventions aimed at improving the STEM education-career pipeline. Prior research has posited that achievement motivation can be represented by four major factors: performance-approach, mastery-approach, performance-avoidance, and mastery-avoidance orientations. The present study tests whether there are distinct math motivation classifications in grades 9 and 11. Classifications at each grade level were tested using responses on seven math motivation 4-point rating scale items from a nationally representative sample of $N = 23{,}503$ (15,605 with complete data at both grades) high school students who participated in the 2009 High School Longitudinal Survey (HSLS:09). Both *k*-means cluster analysis (CA) and latent class analyses (LCA) were used to examine the number and nature of classifications at each grade level separately; next, a latent transition analysis (LTA) was used to test class membership patterns across the two grade levels. LCA results indicated that there were three classes for each grade level, and that the class types appeared to simply quantify sections of a normally distributed motivation factor (low, moderate, and high motivation), rather than qualitatively different classes; the LCA findings were also comparable to the non-model-based CA results. The LTA results showed that, while many adolescents remained stable within their classifications from grade 9 to 11, students in the extremes of grade 9 (low and high motivation classes) tended to move toward moderate motivation by grade 11. Ultimately, a latent growth model treating motivation as continuous rather than nominal had the best fit to the data. Limitations and future research directions are discussed.

Keywords: math achievement, motivation, adolescent, high school, latent class analysis, latent transition analysis, k-means, cluster analysis, complex survey weights

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Why do students decide to study hard for a math test, do their homework, or strive to get the highest grade in the class? Conversely, why do certain students fail to do their homework, not care, or feel as if math is a boring subject? Broadly speaking, the mechanism behind these choices is often termed “motivation.” Quite recently, when compared to reading, writing, and science, math has been shown to have experienced the greatest decline in intrinsic motivation (Gottfried, Fleming, & Gottfried, 2001).

While much of the empirical research (described in the forthcoming) grounded in Achievement Goal Theory (AGT; Dweck, 1986; Nicholl, 1984) has been focused on motivation from a *static* perspective – motivation at a single point in time predicting a concurrent or future achievement outcome – there has been little research for testing whether math motivation might be classified into subtypes that are consistent with AGT, and whether these subtypes persist or change over time. Such subtypes/classes could potentially enable educators to better identify students for tailored motivational interventions; for example, rather than using more of the same “boring” subject to help children achieve in math, perhaps those who are “bored” with math need more applied, concrete experiences to improve achievement. In contrast, a student who already finds math engaging might need more challenging, abstract concepts to work on to continue to engage at a high level.

In the present study, we used data from seven rating scale response items on math motivation to empirically evaluate the number and nature of math motivation classifications present in a nationally representative sample of U.S. students who completed surveys in grades 9 and 11. Classifications were derived using both k-means cluster analysis (a non-model-based algorithm that is easily accessible to most researchers) and latent class analysis (a structural equation model that allows for measurement error and model-based data fit assessment). To test for change over time, a latent transition analysis was used (predicting Grade 11 classifications based on Grade 9 classifications).

Mastery vs. Performance Motivation

Achievement Goal Theory (AGT) describes motivation as “the purposes for behavior that are perceived or pursued in a competence-relevant setting” (Midgley, Kaplan & Middleton, 2001). According to Dweck (1986), there are two main goal orientations under this theory: 1) *mastery* orientation, which is the goal of developing competence (akin to “intrinsic” motivation), and 2) *performance* orientation, which the goal of demonstrating competence (akin to “extrinsic” motivation). Both Dweck (1986) and Nicholls (1984) examined performance and mastery as two separate (additive) orientations, and did not explore whether there was a potential interactive (multiplicative) effect between them on outcomes. Others have suggested instead that mastery and performance should be considered interactive in that they combine in a way that bolsters outcomes better than in isolation (e.g., Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Midgley, Kaplan, & Middleton, 2001; Zusho & Njoku, 2007).

Both Midgley et al. (2001) and Harackiewicz et al. (2002) agree that there is a relationship between mastery and performance goals; however, there is disagreement around whether or not performance goals can be effective with or without mastery goals. Midgley et al. (2001) argue that, when dealing with academic performance, there is a positive interaction between the two goal orientations, and that performance-based goal orientation is effective only when mastery goal orientation is high. Conversely, Harackiewicz et al. (2002) argues that numerous studies have shown a positive main effect of performance goal orientation in the absence of mastery goal orientation. Consistent with Nicholls, Cobb, Wood, Yackley, and Patashnick (1990), Harackiewicz, et al. (2002) posited that a specialized goal orientation *pattern*, where each goal independently predicts separate outcomes, would optimally motivate students.

Approach vs. Avoidance Motivation

Irrespective of whether they are additive or interactive, the mastery and performance orientations in the foregoing are both considered an *approach* type of achievement goal orientation, which means that they are both related to *positive* outcomes for students. Research conducted by Elliot (1999) suggests that both mastery and performance motivation may be related to a negative outcomes as well. Two new dimensions were thus coined as *approach* (positive, success) vs. *avoidance* (negative, failure) goal orientations, both of which can be applied to mastery and performance orientations to form four types of motivation: performance-approach, mastery-approach, performance-avoidance, and mastery-performance (Elliot & McGregor, 2001). While this framework retained the idea that performance and mastery approaches were additive rather than interactive, it allows students to be measured and identified in a manner more consistent with realistic motivational constructs.

Motivation Orientations and Math Achievement

Given that both performance- and mastery-approach orientations have been shown to positively correlate with achievement outcomes, knowing which orientation leads to different kinds of achievement outcomes can enable educators to better tailor instruction and interventions to students with specific orientations. Most recently, Keys, Conley, Duncan, and Domina (2012) compared mastery-approach, performance-approach, and performance-avoidance orientations (as classified by a motivation survey instrument; notably the master-avoidance orientation was not considered in this study) on norm-referenced standardized math test scores for seventh and eighth grade students. Surprisingly, their results showed that only the mastery-approach orientation was significantly predictive of math achievement; performance-approach and performance-avoidance were not. In explaining their findings, the researchers speculated that their sample was potentially not representative of the full range of each motivation orientation, and that future research was warranted. It is also possible that the survey measuring motivation orientations was imprecise and/or that the norm-referenced test only measured one aspect of mathematics achievement that students had been working on (thus, not fully capturing the kind of achievement that performance-based motivations would tap into).

Changes in Motivation over Time

In addition to understanding motivation orientations and their links with achievement outcomes, there is also a need to understand whether motivation is static or changes over time, particularly during childhood and adolescence. Gottfried, Marcoulides, Gottfried, Allen, Oliver, and Guerin (2007) conducted an analysis on data from Fullerton Longitudinal Study that followed U.S. students from birth through the end of high school on math motivation and achievement variables (subjects were selected for participation at birth but measurement began at 9 years of age). The research utilized a latent variable model (structural equation modeling framework) to evaluate the relationship between changes in academic intrinsic motivation as assessed with the *Children's Academic Intrinsic Motivation Inventory* (Gottfried, 1986) (treated as a single construct on a normal continuum; variables used were not necessarily grounded in achievement goal theory) and changes over time in achievement (again, treated as a single construct on a normal continuum, using the *Woodcock-Johnson Psycho-Elementary Battery* (Woodcock & Johnson,1989). The study findings revealed that, as math achievement declines, so too does intrinsic motivation (or vice versa, as they both co-occur together). More concerning, the decline in intrinsic motivation was found to start in early elementary school.

Similarly, Marcoulides, Gottfried, Oliver, and Gottfried (2008) utilized the same data as Gottfried et al. (2007), but applied a latent class analysis (LCA) and latent transition analysis (LTA) to understand what *classes* of intrinsic motivation existed among students, and whether those motivation *classes* changed over time. Their findings suggested that there are three distinct classes of intrinsic motivation: intermediate, at-risk, and gifted classes, and that changes in class membership occurred primarily between the ages of 9-13 years old; thereafter, class membership became more stable as students enter into high school (i.e., little change during high school). In contrast to Marcoulides et al. (2008) findings (but consistent with Gottfried et al., 2007), Chouinard and Roy (2008) found that math motivation (using items grounded in achievement goal theory, rather than just intrinsic motivation variables) did decline during high school for a Canadian student sample, as did math achievement.

The 2009 High School Longitudinal Study Dataset

The National Center for Educational Statistics (NCES) High School Longitudinal Study of 2009 (HSLS:09; Ingels, Pratt, Herget, Dever, Fritch, Ottem & Leinwand, 2014) is a nationally representative dataset that tracked the same cohort of high school students from Fall of 2009 when they were freshmen to Spring of 2012 when they were seniors. It contains a wide variety of items but its primary focus was on student-level STEM education variables; most years the survey included the same variables and items, but inevitably some items were changed, dropped, or added. Prior research using this dataset has indeed focused on math motivation (e.g., Andersen & Cross, 2014; Froiland, & Davison, 2016; Froiland, Davison, & Worrell, 2016; Middleton, 2013), but none thus far has evaluated math motivation classes or changes in math motivation classes over time.

Middleton's (2013) study focused on modeling numerous ninth grade math motivation variables to develop novel math motivation subconstructs, including: identity, interest, utility, and self-efficacy, as well as general effort. Math *identity* was based on the idea that a student or others see themselves as a math person; *interest* was based on math enjoyment on the positive side and math is a waste of time and boring on the negative side; *utility* was the usefulness of math in everyday life, college, and future career; *self-efficacy* was defined by confidence and mastery around mathematics; and *general effort* was based on class preparedness and punctuality. The study's primary goal was to measure the relationships among these motivational subconstructs and determine their unique effects on achievement.

Andersen and Cross (2014) conducted a study focusing on whether high-ability math students were different from others in their STEM motivation profile. They specifically examined the first wave of the HSLS:09 data (ninth graders) and estimated latent class membership separately for math and science based on measures of self-efficacy, attainment, utility, interest, and enjoyment. For both math and science domains, they found that a four-class model fit the data best, which included low, typical, and two high-end motivation classes. In addition, their findings showed that students that had high math ability tended to have high math motivation, but that with high math ability were actually low in motivation.

In more recent study, Froiland and Davison (2016) showed that grade 9 parent, student, and peer expectations predicted grade 9 intrinsic motivation, which in turn predicted grade 11 intrinsic motivation. In addition, their findings showed that intrinsic motivation predicted math course-taking and achievement (achievement was measured with an online algebraic reasoning assessment administered by the NCES and RIT International). In a smaller study, Froiland and colleagues (Froiland, Davison, & Worrell, 2016) used a sub-sample of the HSLS:09 data to explore Hawaiian students' teaching culture on intrinsic motivation.

Present Study

While previous studies have utilized the HSLS:09 dataset to examine math motivation and achievement, none have used the data to investigate motivation classes at grade 9 and 11 and whether those students change class memberships over time (i.e., as Marcoulides et al. (2008) did in their study, and as Anderson and Cross (2014) started to do with the grade 9 HSLS:09 data). The present study will thus contribute to the literature by examining the HSLS:09 data for this same purpose; whereas Marcoulides et al. found three classes along a continuum of math motivation (as did Anderson and Cross with the 9th grade sample alone), we hypothesized that we might find classes that are representative of three of the achievement goal orientations: performance-approach, mastery-approach and performance-avoidance.

In addition to our substantive interest in motivation classes, it was of methodological interest to evaluate whether a *k*-means cluster analysis would yield similar results to a latent class analysis of these data given the ease of access to, and computation of, CA compared to LCA. It is well known that *k*-means CA is limited to using either all dichotomous variables or all continuous variables (rather than a mix of variable types as LCA can handle), and it is also limited in that it assumes no measurement error (unlike LCA) and cannot help the researcher understand whether the clusters represent the data well as it is algorithmic rather than model-based (Magidson & Vermunt, 2002). Despite its advantages over CA, LCA however requires statistical education, software access, and software training; as such, it may be much less appealing for many analysts looking for more "quick" answers, and if CA results are similar to

LCA, then it would not be a bad option. For example, a recent study in the realm of marketing (Vidden, Vriens & Chen, 2016) compared CA clusters with LCA classes and found the LCA to be superior in categorization of market segments, but that the clusters and classes were well correlated. A similar study by Munson, Dawson, Sterling, Beauchaine, Zhou, Koehler, Lord, Rogers, Sigman, Estes, and Abbott (2008) estimated classifications for children with Autism Spectrum Disorder (ASD) using a battery of assessments; they too found that the LCA results were similar but superior to the CA results.

Research Questions

Using the HSLS:09 dataset, the present study focuses on investigating the following two research questions.

1) What is the number and nature of latent classes for math achievement motivation in Grades 9 and 11 when identified using a Latent Class Analysis, compared with a k-means cluster analysis?
2) Do students change their math motivation latent classes between Grades 9 and 11? In other words, is latent class membership relatively stable over this period of time, or is it transitive?

Methods

Dataset

Extant data from the National Center for Educational Statistics (NCES) High School Longitudinal Study of 2009 (HSLS:09) was used for analyses. This study tracked students who started their freshman year of high school in fall 2009, and continued measuring students annually through spring 2012 (Ingels, Pratt, Herget, Dever, Fritch, Ottem, & Leinwand, 2014). The study sampled 23,503 students across 944 schools, of which 51% were male and 49% were female. The data collected was primarily focused on students' pursuits (post-secondary and career) and motivations in mathematics and the sciences. In addition to student measures, the study also surveyed teachers, parents, administrators and academic support personnel.

For this study, we were interested in investigating the number and nature of math motivation classes in grade 9 (measured in 2009) and grade 12 (measured in 2012), and whether students change class membership between these years. The initial 2009 sample included 19,022 students who were nationally representative of the U.S. public high school population; the 2012 sample included 17,306 students; the difference in the sample from 2009 to 2012 can be attributed to students moving, dropping out of high school, becoming deceased, or not taking a math class in one of the two periods (importantly, this latter reason for missingness may be a limitation in our findings). The publicly available dataset, which includes student-level data without high school identifiers, was used for analyses; however, the longitudinal complex sample survey weight (variable *W2W1STU*) was incorporated into all latent class models to control for potential non-independence of students within high schools.

Measured Variables

The HSLS:09 data used in the present study included math motivation self-report survey items that were worded exactly or nearly exactly at grades 9 and 12. Although dichotomous measures were available, to ensure comparability of CA and LCA analysis methods, we selected only items that were rated on a 4-point scale (1 = *Strongly Disagree* to 4 = *Strongly Agree*). In addition, items were chosen based on whether they fit with one of the three major achievement goal orientations: math mastery-approach, math performance-approach, and math performance-avoidance (there were no items to fit math mastery-avoidance). Specifically, *math performance-voidance* included two items associated with negative associations, including math is boring and math is a waste of time; *math mastery-approach* included two items associated with mastering concepts, including mastering skills taught and understanding the math textbook; finally, *math performance* was measured with two items associated with performing well, including excellent performance on math tests and math assignments. In the dataset, these variables included the following 14 variables (note that the first two items for each grade level were negative).

1. S1MWASTE - S1 C06B 9th grader thinks fall 2009 math course is a waste of time
2. S1MBORIN - S1 C06C 9th grader thinks fall 2009 math course is boring
3. S1MENJOY - S1 C06A 9th grader is enjoying fall 2009 math course very much
4. S1MTEXTB - S1 C08B 9th grader certain can understand fall 2009 math textbook
5. S1MSKILL - S1 C08C 9th grader certain can master skills in fall 2009 math course
6. S1MTESTS - S1 C08A 9th grader confident can do excellent job on fall 2009 math tests
7. S1MASSEX - S1 C08D 9th grader confident can do excellent job on fall 2009 math assignments
8. S2MWASTE - S2 D20C Teen thinks (spring 2012) math course is a waste of time
9. S2MBORING - S2 D20F Teen thinks (spring 2012) math course is boring
10. S2MENJOYING - S2 D20A Teen is enjoying (spring 2012) math course
11. S2MTEXTBOOK - S2 D20B Teen certain can understand (spring 2012) math textbook
12. S2MSKILLS - S2 D20D Teen certain can master skills taught in (spring 2012) math course
13. S2MTESTS - S2 D20E Teen confident can do an excellent job on (spring 2012) math tests
14. S2MASSEXCL - S2 D20G Teen confident can do excellent job on (spring 2012) math assignments

Data Analysis Plan

Software. Latent variable models were conducted in *Mplus 7.2* (Muthén & Muthén, 1998-2014), and descriptive analyses were conducted in *SPSS 19* (SPSS Inc., 1989-2010).

Latent Class Analysis. Latent class analysis (LCA), which is also known as a mixture model, is a tool that allows us to estimate unobserved groupings in the data based on our seven measured motivation variables. LCA specifically estimates the probability of individuals belonging to a specific multivariate distribution among a set of distributions in the data. A 2-, 3- and 4-class model were specified for each of the two grade levels, and for all models, the HSLS:09 longitudinal sampling weight was incorporated. To determine the model of best fit for each grade level, fit indices were employed, including the Bayesian information criterion (BIC), Akaike's information criterion (AIC), and entropy, in conjunction with relative model fit tests as assessed by the Lo-Mendell-Rubin likelihood ratio test (LRT). The BIC for example is utilized for balancing model fit and parsimony in which a smaller BIC number represents a better fit (Collins & Lanza, 2010; Vrieze, 2012). The Lo-Mendell-Rubin LRT (Lo, Mendell, & Rubin, 2001) compares whether a *k*-class solution fits better than a *k*-1 class solution, i.e. if a 4 class solution fits better than a 3 class solution. In LCA analyses, entropy is a statistic that summarizes the overall probability of classification of individuals to each of their respective classes; values can range from 0 to 1, and higher values are better (Ramaswamy, Desarbo, Reibstein & Robinson, 1993). In addition to fit indices and LRT results, model convergence issues also played a role in model selection (e.g., non-positive definite variance-covariance matrices are indications of model instability; the model is overly complex for the data available). See Figure 1 for example of the path diagram for the 2-class vs. 3-class LCAs.

***K*-Means Cluster Analysis.** Similar to the LCAs at grades 9 and 11, a *k*-means cluster analysis (CA) was applied to each grade level separately for direct comparison with the LCA results. There are many CAs, but the *k*-means CA is an algorithm that seeks to maximally separate subjects into a discrete set of groupings based on a set of measured variables; the algorithm specifically minimizes within-group distances to the centroid (of the set of measured variables) while maximizing between-group distances (MacQueen, 1967); the distances are typically based using Euclidian distance (Danielsson, 1980). In *k*-means CA, deciding the value of *k* clusters for a given dataset is subjective (Steinley & Brusco, 2011), thus it is suggested that it should be determined based on theory or some other prior analysis. Furthermore, as already mentioned, *k*-means CA is limited to either all continuous, or all binary, variables (Holmes & Huynh, 2005).

Latent Transition Analysis. Finally, latent transition analysis (LTA) was employed to test change over time. The number of classes to specify were determined by our prior LCA results; and can be thought of as a longitudinal model extension of LCA. The model posits that an unobserved set of categories (i.e., groupings; in this case, grade 11 motivation classes) can be predicted from a set of categorical indictors (i.e., other groupings; in this case, grade 9 motivation classes). As with the LCA models, LTA has fit indictors to evaluate model fit; however our focus for the LTA will be less on fit and more on the changes in latent class membership. Specifically, LTA results will shed light on the number of students that stay in a specific class, known as "stayers," as well as those that move from one class to another, or "movers." For movers, we shall also be able to determine the direction of change.

Results

Weighted Descriptive Statistics

Weighted descriptive statistics for the seven observed variables are provided in Table 1 by grade level; weighted correlations among all fourteen variables are provided in Table 2.

Latent Class Analysis (LCA) Results for Grades 9 and 11

A total of three latent class analysis (LCA) models were specified separately for grades 9 and 11 using the set of respective seven motivation variables for that grade in order to determine the best fitting model. Results are displayed in Tables 3 and 4 for grades 9 and 11, respectively. For grade 9, the entropy was maximized to 99% with a 3-class model. Despite the BIC preferring a 4-class model over the 3-class model, the Vuong-Lo-Mendell-Rubin and LoMendell-Rubin Adjusted LRT tests indicated that the 4-class model did not fit better than a 3-class model ($p > 0.05$), and further, the 3-class model was a better fit than a 2-class model ($ps < .0001$). Given the evidence, the 3-class model was determined to be the best fit for the 9th grade wave. For the 11th grade model, the BIC and entropy indicated that the 3-class model was preferred over the 2-class model (as did the LRT tests), and further, the 4-class model become unstable. Hence, we retained the 3-class model as the best model for the 11th grade items as well.

For both grade levels, we had theorized that a three-class model would emerge to represent the three types of achievement goal theory discussed earlier: that is, performance-avoidance, mastery-approach, and performance-approach orientations of motivation. When we examined the loading magnitudes and patterns for each of the three classes, for each grade level, we saw that only one of the three classes mapped as expected: specifically, the performance-avoidance (or “low”) motivation class was linked with the two negatively worded items (math is boring and math is a waste of time). The remaining two profiles did not map as expected, and instead we saw that the items that were theoretically associated with mastery-approach and performance-approach loaded together near average on Class 2 (recall that the items were standardized as part of the analysis) and loaded together in high magnitudes on Class 3 (see Tables 5 and 6 for loading estimates for grades 9 and 11, respectively; see also Figure 2 for a graphical display of patterns). Thus, based on these results the final classes can be categorized as follows “low,” “moderate,” and “high” motivation levels, consistent with prior research that attempted to classify students into motivation categories using items such as these.

K-means Cluster Analysis Results and Comparison with LCA Classes

To get a sense for the classification accuracy of an algorithmic *k*-means cluster analysis (CA) compared to our model-based LCA results (which allowed for measurement error) a *k*-means CA was conducted for the grade 9 and 11 data (separately). The CA’s predicted cluster memberships were then compared to the LCA-predicted student classifications (posterior predicted probability that assigns students to the class based on their highest likelihood of class membership). As can be seen in Table 7, proportions of students assigned to cluster as well as the means on the items for students within clusters were similar to those of the LCA classes. For students with complete data at both time points, Spearman's rho = 0.75 for grade 9 clusters with classes, and 0.76 for grade 11 clusters with classes ($ps < .05$). Thus, it appears that CA might be a viable option for analysts to use when LCA is not, at least in the case of continuous indicator variables.

Latent Transition Analysis Results

Based on our LCA findings, we conducted a latent transition analysis (LTA), assuming three classes at each of the two grade levels. The LTA specifically allowed us to examine the changes in math motivation classifications from grade 9 to 11 (see Figure 3 for illustration of path diagram of model). The model entropy was 0.87, which indicates that the overall probability of the sensitivity and specificity of classifying students into one of nine classification patterns is 87%. The model-estimated posterior proportions of each pattern of classes is shown in Table 8, and Table 9 displays the mean probability of a particular class occurring in the sample across grades 9 and 11. As can be seen in Table 9, for the extreme classes (Class 1 and 3, low and high motivation, respectively) there is more variability in whether a student will transition from their grade 9 classification into another class by grade 11. In Table 10, we see that the mean precision of class membership assignment was generally quite high (≥ 0.83), but most precise for Class 2.

If we examine the mean predicted proportions of class membership at each grade level shown in Figure 4 (these probabilities those that were jointly, rather than separately, estimated), we see that most of the sample stays within their original predicted class membership (59%), and those who changed tended to move up in their motivation classification (24%) rather than down (18%). Another way to examine these data is to look at the proportion of changes over time *within* a given original grade 9 classification (see Figure 5); further, we can distill these proportions into those who *increased* their motivation compared to those who decreased or stayed the same (noting of course that Class 1 can only move into a higher class if there is any movement, and that Class 3 can only move into a lower class if there is any movement). As can be seen, for the low motivation class, 42% of grade 11 students stayed within their original grade 9 classification, while 51% moved into the moderate class, and 7% moved into the high motivation class. For Class 2 (moderate motivation), the model predicted 72% stayed in the same class, while 16% moved lower class and 11% moved higher. Finally, 35% stayed in the highest motivation class while 56% moved into the moderate and 9% moved into the low class.

Discussion

Findings from the current study revealed that there are three types of high school student motivation types in both grades 9 and 11. In addition, predicted model-based class memberships matched well with the cluster designations derived from *k*-means cluster analyses (CA) of the same data. Finally, latent transition analysis results indicated that, while over half of students were predicted to stay in the same class from grade 9 to 11, a good proportion were predicted to change class membership.

The finding that the *k*-means CA yielded similar results to the latent class analyses (LCAs) was not surprising (see for example Vidden, Vriens, & Chen, 2016). A more important and somewhat surprising result was that, while the three-class model at each grade level was our hypothesized *number* of classes, the *nature* of these classes were not as anticipated. We believed that the items used in analyses represented three kinds of motivation orientations: performance-avoidance, performance-approach, and mastery-approach (no items fit the fourth type, mastery-avoidance, in achievement goal theory literature). Instead, the 3-class model at each grade level, based on the loading patterns, showed that each class appeared to represent a continuum of a general motivation construct, with low (performance-avoidance), moderate (a combination of both approach types), and high motivation (again, a combination of both approach types) motivation levels. To further test this idea, we conducted a post-hoc analysis of the data treating the set of grade 9 variables as measuring a single continuous motivation construct at that time period, and predicting grade 11 motivation (treating the set of grade 11 variables as measuring a single continuous motivation construct at that time period; code provided in Appendix) had a far better fit to the data (BIC decrease of 6,992 points compared with the LTA model, which is far greater than the 10-point decrease decision rule for a preferred model), had a near-optimal square root mean residual value of .07 (.05 or lower preferred), and showed that the overall latent motivation variable in grade 9 was predicted to correlate with the latent motivation in grade 11 at $r = 0.40$ ($p < 0.05$).

Our finding that the nature of the latent variable at each grade level is more likely to be continuous than qualitative/categorical is also consistent with two prior studies. Recall that Marcoulides, Gottfried, Oliver, and Gottfried (2008), who found that an LCA of a different longitudinal dataset's variables using both achievement and motivation items revealed four classes of motivation: low ("at-risk"), moderate ("intermediate"), and two higher end classes ("gifted"). In addition, their class size proportions were similar to those found here: at age 16, 24% were "at risk," 55% were "intermediate," and 21% were "gifted." Also recall that a study of the present dataset (using far more variables than the current study) for grade 9 also yielded math motivation classes that included low, moderate ("typical"), and high levels (Andersen & Cross, 2014). This said, the present study is limited to (a) math motivation, and (b) the items used to measure motivation; more discussion of this is forthcoming.

The final finding of interest is that the results from the LTA suggest that, while there is evidence for greater stability than change in class membership from grades 9 to 11, there is also evidence for some change during this period of adolescence. As can be seen in Figure 5, there was more positive than negative change predicted, and as can be seen in Figure 3, the most change that occurred within a given class was in the poles of the classes (low and high motivation classes). This finding is in line with the Canadian-based study by Chouinard and Roy (2008) who found that motivation does increase during the high school years. Our results are also consistent with Gottfried et al.'s (2007) suggestion that there is also quite a bit of stability in motivation levels during high school.

Limitations and Future Research Directions

This research utilized the publicly available data from the HSLS:09 study. As such, school identifiers were not available to be used in the analysis, which did not us allow to account for school membership, aggregate school-level environmental contexts, or individual-level GPA of math courses. Having this data would allow us to better analyze the data for context effects on student motivation (and avoid use of the sampling weight, which can limit analysis estimation choices), as well as understand if math course grade point average (GPA) is related to math motivation (we can test questions such as whether performance in math at one time point changes student motivation at another time point – i.e., incorporating extrinsic motivation).

In addition to the dataset constraints, we also limited analyses to only rating scale variables so that we could compare *k*-means CA with LCA findings. This naturally constrained the kinds of items that could be incorporated as well as the number of items to be incorporated in measuring the latent motivation variable. Future research should include a mix of all possible variables that are related to achievement motivation theory. Last but not least, this research only focused on math as a domain, and only for U.S. high school students in public high schools in grades 9-12. Thus, any generalizations from this study are limited to math motivation during this period of education.

Conclusion

One potential implication for this study is that it appears that students are not entirely stable in their motivation levels from grade 9 to 11. This means that there is opportunity for malleability of motivation. We might ask what interventions might be desirable for certain individuals, particularly those in the lower grade 9 classification of motivation to move upward, and those in the moderate and high levels to at least remain (i.e., not move downward). In addition, the findings also suggest that, with these recent data, there continues to be a deficit in math motivation. It is possible that the current advocacy for increased and improved STEM education may not be as effective as we might hope, given that the largest class in the sample (moderate motivation) had relatively flat means on the motivation rating scale items. Perhaps, in addition to setting high standards around required math courses, it may be fruitful to re-examine how to make those courses more engaging and rewording, to improve both intrinsic and extrinsic motivation toward math achievement.

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Table 1.

Weighted Motivation Item Descriptive Statistics

	Grade 9		Grade 11		*Approx.*
Item	*M*	*(SD)*	*M*	*(SD)*	*d*
Math waste of time* - *Avoid*	3.15	(0.80)	2.98	(0.84)	-0.21
Math is boring* - *Avoid*	2.63	(0.90)	2.42	(0.90)	-0.23
Enjoying math- *Mastery*	2.25	(0.84)	2.54	(0.93)	0.33
Understand math book - *Mastery*	2.30	(0.82)	2.47	(0.88)	0.20
Master math skills - *Mastery*	2.04	(0.73)	2.18	(0.78)	0.19
Math test confident - *Perf*	2.05	(0.76)	2.25	(0.82)	0.25
Math assignments confident - *Perf*	1.95	(0.71)	2.11	(0.77)	0.22

Note. All items rated on a 1-4 scale. Approx. *d* calculated as the mean difference of the grades divided by the average of the standard deviations across grades.
* negative item

Table 2.

Weighted Zero-order Correlations among Motivation Items

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
Grade 9													
1. Math waste of time* - *Avoid*	--												
2. Math is boring* - *Avoid*	0.56	--											
3. Enjoying math- *Mastery*	-0.50	-0.57	--										
4. Understand math book - *Mastery*	-0.23	-0.28	0.43	--									
5. Master math skills - *Mastery*	-0.30	-0.30	0.45	0.66	--								
6. Math test confident - *Perf*	-0.29	-0.31	0.48	0.67	0.69	--							
7. Math assignments confident - *Perf*	-0.32	-0.32	0.48	0.63	0.72	0.74	--						
Grade 11													
8. Math waste of time* - *Avoid*	0.23	0.19	-0.18	-0.13	-0.15	-0.15	-0.16	--					
9. Math is boring* - *Avoid*	0.17	0.21	-0.19	-0.13	-0.15	-0.15	-0.14	0.56	--				
10. Enjoying math- *Mastery*	-0.15	-0.21	0.28	0.22	0.22	0.23	0.22	-0.42	-0.59	--			
11. Understand math book - *Mastery*	-0.12	-0.16	0.22	0.28	0.26	0.26	0.24	-0.26	-0.32	0.59	--		
12. Master math skills - *Mastery*	-0.13	-0.15	0.19	0.25	0.28	0.26	0.25	-0.31	-0.30	0.52	0.62	--	
13. Math test confident - *Perf*	-0.09	-0.13	0.19	0.26	0.26	0.29	0.26	-0.30	-0.31	0.55	0.64	0.72	--
14. Math assignments confident - *Perf*	-0.13	-0.14	0.21	0.26	0.28	0.28	0.28	-0.32	-0.30	0.54	0.61	0.70	0.76

Note. All items rated on a 1-4 scale.
* negative item

Table 3.

Grade 9 Latent Class Model Fit Indices

Model	*No. Parms*	*Log Likelihood*	*AIC*	*BIC*	*Adj BIC*	*LRT p-value*	*Entropy*
1 Class	14	-188,904	377,835	377,945	377,901	--	--
2 Classes	22	-172,938	345,921	346,093	346,024	<.001	0.84
3 Classes	30	-156,607	313,273	313,509	313,414	<.001	0.99
4 Classes	38	-154,583	309,242	309,541	309,420	n.s.	0.90

Table 4.

Grade 11 Latent Class Model Fit Indices

Model	*No. Parms*	*Log Likelihood*	*AIC*	*BIC*	*Adj BIC*	*LRT p-value*	*Entropy*
1 Class	14	-198,612	397,251	397,362	397,317	*na*	*na*
2 Classes	22	-178,519	357,082	357,256	357,186	<.001	0.86
3 Classes	30	-169,133	338,326	338,563	338,468	<.001	0.92
4 Classes	--	--	--	--	--	--	--

Table 5.

Grade 9 3-Class LCA Model Estimated Loadings and Predicted Class Percentages

Class, Item	*Loading*	*(SE)*	*p*
Low Motivation (n = 4,302 students, 25.1%)			
Math waste of time* - *Avoid*	0.34	(0.02)	<.001
Math is boring* - *Avoid*	0.36	(0.03)	<.001
Enjoying math- *Mastery*	-0.59	(0.02)	<.001
Understand math book - *Mastery*	-0.90	(0.02)	<.001
Master math skills - *Mastery*	-1.01	(0.02)	<.001
Math test confident - *Perf*	-1.01	(0.02)	<.001
Math assignments confident - *Perf*	-1.33	(0.00)	<.001
Mod Motivation (n = 8,842 students, 58.0%)			
Math waste of time* - *Avoid*	0.04	(0.02)	0.041
Math is boring* - *Avoid*	0.02	(0.02)	n.s.
Enjoying math- *Mastery*	-0.01	(0.02)	n.s.
Understand math book - *Mastery*	0.10	(0.01)	<.001
Master math skills - *Mastery*	0.10	(0.01)	<.001
Math test confident - *Perf*	0.08	(0.01)	<.001
Math assignments confident - *Perf*	0.07	(0.00)	<.001
High Motivation (n = 2,461 students, 16.9%)			
Math waste of time* - *Avoid*	-0.62	(0.04)	<.001
Math is boring* - *Avoid*	-0.61	(0.03)	<.001
Enjoying math- *Mastery*	0.89	(0.03)	<.001
Understand math book - *Mastery*	1.01	(0.02)	<.001
Master math skills - *Mastery*	1.14	(0.03)	<.001
Math test confident - *Perf*	1.23	(0.03)	<.001
Math assignments confident - *Perf*	1.72	(0.02)	<.001

Note. All items rated on a 1-4 scale. * negative item

Table 6.

Grade 11 3-Class LCA Model Estimated Loadings and Predicted Class Percentages

Class, Item	*Loading*	*(SE)*	*p*
Low Motivation (n = 3,072 students, 19.69%)			
Math waste of time* - *Avoid*	0.45	(0.03)	<.001
Math is boring* - *Avoid*	0.57	(0.04)	<.001
Enjoying math- *Mastery*	-0.95	(0.03)	<.001
Understand math book - *Mastery*	-1.16	(0.02)	<.001
Master math skills - *Mastery*	-1.26	(0.02)	<.001
Math test confident - *Perf*	-1.31	(0.02)	<.001
Math assignments confident - *Perf*	-1.30	(0.02)	<.001
Mod Motivation (n = 9,028 students, 57.8%)			
Math waste of time* - *Avoid*	0.11	(0.01)	<.001
Math is boring* - *Avoid*	0.05	(0.02)	0.095
Enjoying math- *Mastery*	-0.10	(0.02)	<.001
Understand math book - *Mastery*	-0.06	(0.01)	<.001
Master math skills - *Mastery*	-0.08	(0.01)	<.001
Math test confident - *Perf*	-0.10	(0.01)	<.001
Math assignments confident - *Perf*	-0.14	(0.01)	<.001
High Motivation (n = 3,505 students, 22.4%)			
Math waste of time* - *Avoid*	-0.61	(0.03)	<.001
Math is boring* - *Avoid*	-0.55	(0.03)	<.001
Enjoying math- *Mastery*	0.95	(0.02)	<.001
Understand math book - *Mastery*	1.01	(0.02)	<.001
Master math skills - *Mastery*	1.14	(0.03)	<.001
Math test confident - *Perf*	1.22	(0.02)	<.001
Math assignments confident - *Perf*	1.31	(0.03)	<.001

Note. All items rated on a 1-4 scale. * negative item

Table 7.

Comparison of CA and LCA Post-Analysis Predicted Classifications

	Grade 9						Grade 11					
Items	*k*-Means			LCA			*k*-Means			LCA		
	Clust1	Clust2	Clust3	Class1	Class2	Class3	Clust1	Clust2	Clust3	Class1	Class2	Class3
Math waste of time* - *Avoid*	**3.56**	**3.27**	2.41	**3.43**	**3.18**	2.71	**3.51**	2.91	2.25	**3.42**	**3.10**	2.44
Math is boring* - *Avoid*	**3.16**	2.78	1.70	2.98	2.66	2.13	**3.10**	2.17	1.68	2.95	2.47	1.88
Enjoying math- *Mastery*	1.57	2.18	**3.22**	1.74	2.25	2.96	1.69	2.76	**3.61**	1.66	2.46	**3.44**
Understand math book - *Mastery*	1.46	2.41	**3.01**	1.54	2.38	**3.11**	1.77	2.56	**3.51**	1.45	2.42	**3.40**
Master math skills - *Mastery*	1.26	2.11	2.71	1.29	2.10	2.85	1.59	2.17	**3.11**	1.18	2.09	**3.07**
Math test confident - *Perf*	1.24	2.11	2.78	1.28	2.10	2.94	1.60	2.28	**3.26**	1.16	2.17	**3.25**
Math assignments confident - *Perf*	1.17	2.03	2.64	1.00	2.00	**3.17**	1.54	2.09	**3.06**	1.10	1.99	**3.11**
Mean of Positive Items	*1.34*	*2.17*	*2.87*	*1.37*	*2.16*	*3.00*	*1.64*	*2.37*	*3.31*	*1.31*	*2.22*	*3.25*
Mean of Negative Items	*3.36*	*3.03*	*2.06*	*3.20*	*2.92*	*2.42*	*3.31*	*2.54*	*1.96*	*3.18*	*2.78*	*2.16*

Note. All items rated on a 1-4 scale.
* negative item

Table 8.

LTA Posterior Probability Patterns based on Total Sample Size across Grades

Pattern Number	Grade 9 Class	Grade 11 Class	% of Sample
1	1	1	8%
2		2	10%
3		3	2%
	Total		*20%*
4	2	1	9%
5		2	44%
6		3	12%
	Total		*65%*
7	3	1	1%
8		2	7%
9		3	8%
	Total		*16%*
Proportion Stable			*59%*
Proportion Move Down			*18%*
Proportion Move Up			*24%*

Table 9.

Estimated Latent Transition Probabilities from Grade 9 to 11

		Grade 11		
		Class 1 (Low)	Class 2 (Mod)	Class 3 (High)
Grade 9	Class 1 (Low)	**41%**	49%	10%
	Class 2 (Mod)	15%	**67%**	18%
	Class 3 (High)	8%	46%	**46%**

Note. Diagonals in boldface indicate the predicted probability of a student remaining in the their Grade 9 classification at Grade 11.

Table 10.

Latent Transition Model-Predicted Precision of Student Being Classified Well into the Class Assigned

		Grade 11		
		Class 1 (Low)	Class 2 (Mod)	Class 3 (High)
Grade 9	Class 1 (Low)	95%	90%	90%
	Class 2 (Mod)	85%	89%	83%
	Class 3 (High)	86%	90%	91%

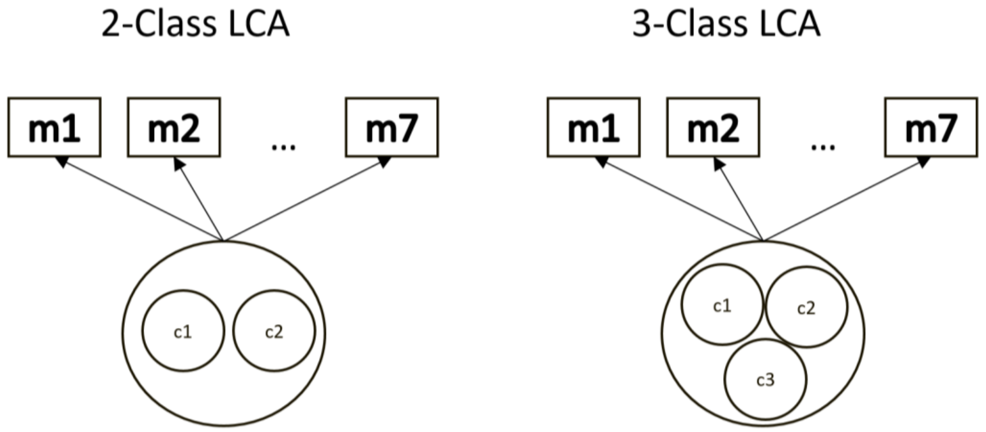
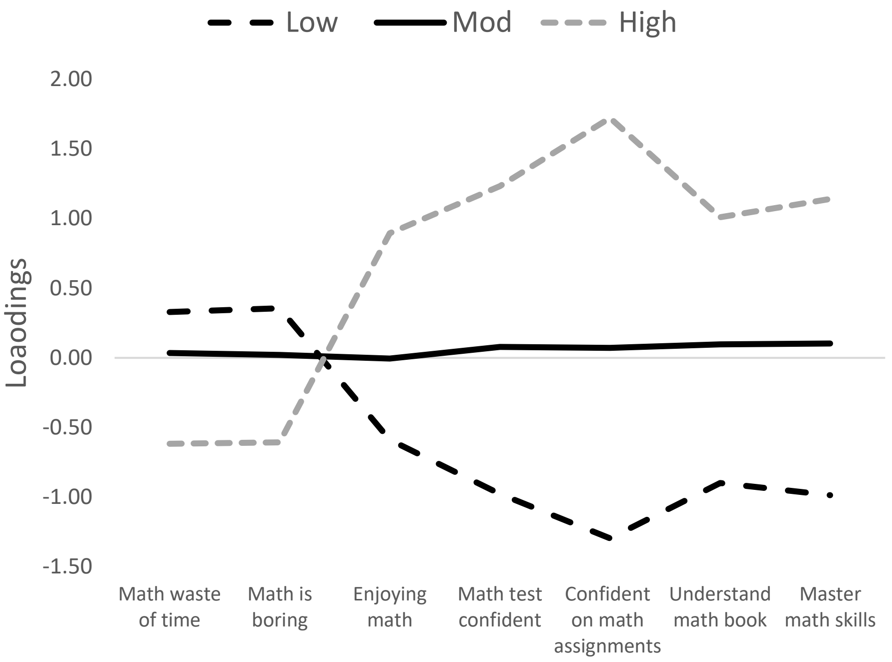


Figure 1. Path Diagram of 2-Class Latent Class Analysis (LCA) (left) and 3-Class LCA (right).

Panel A (Grade 9)



Panel B (Grade 11)

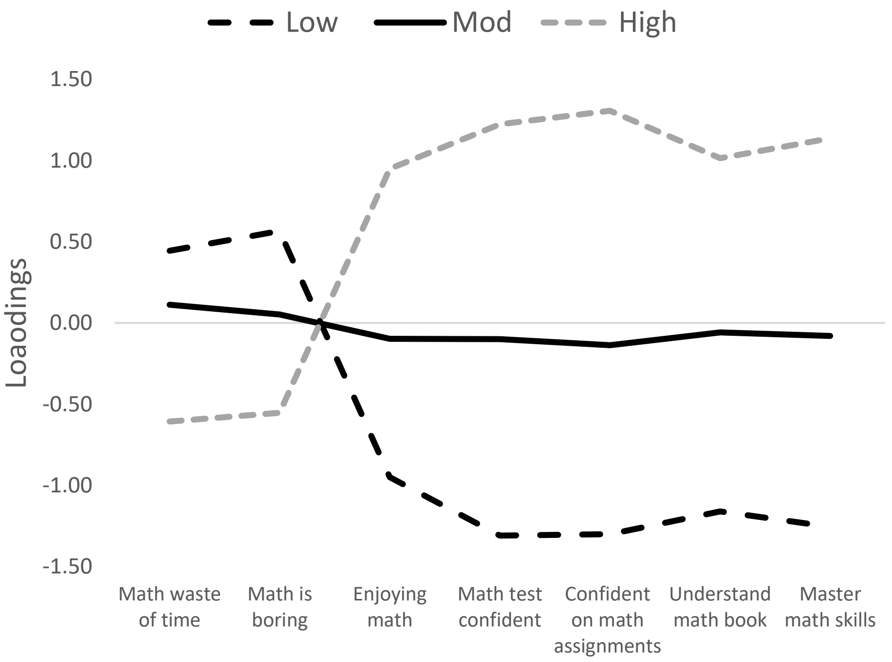


Figure 2. Estimated Loadings for 3-Class Latent Class Analysis Models for Grade 9 (Panel A) and Grade 11 (Panel B)

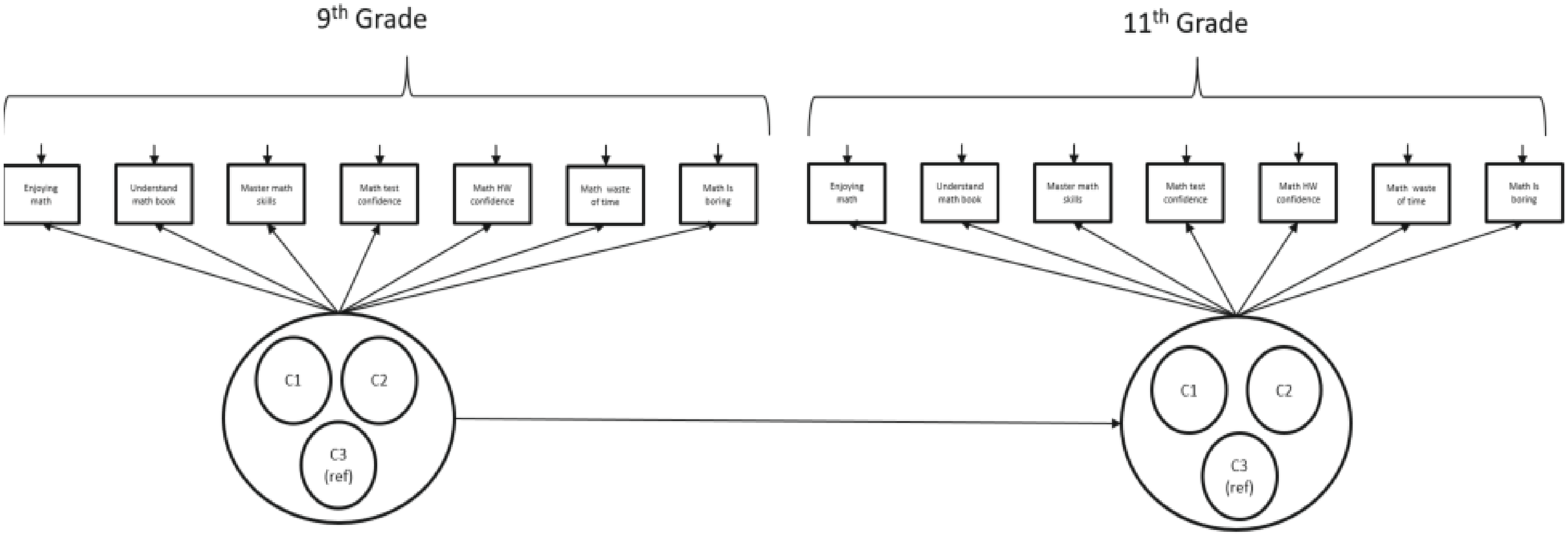


Figure 3. Path Diagram of Latent Transition Analysis Model assuming Three Classes per Grade Level

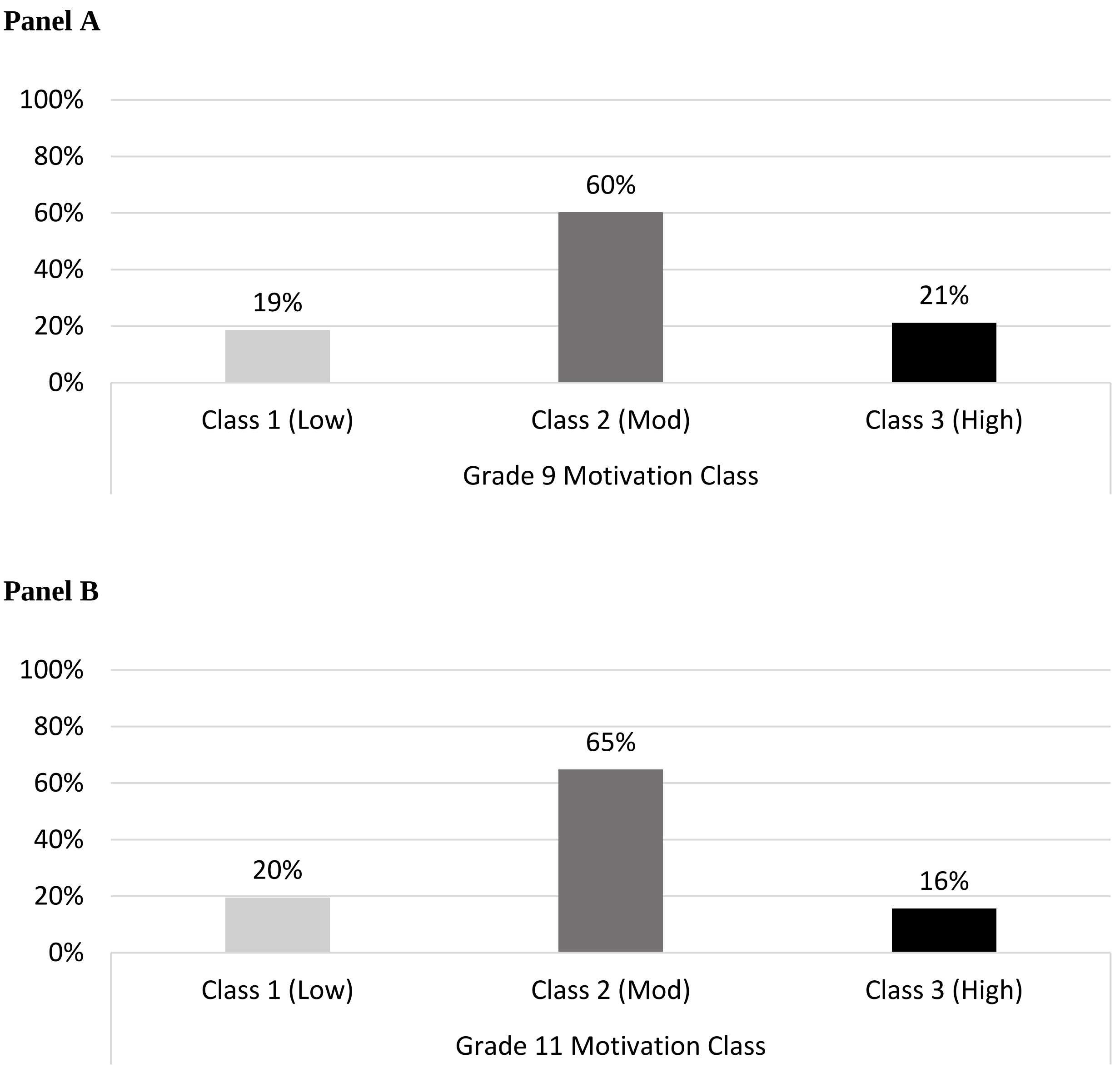


Figure 4. Latent Transition Analysis (Joint) Model-Predicted Student Classifications for Grades 9 (top) and 11 (bottom)

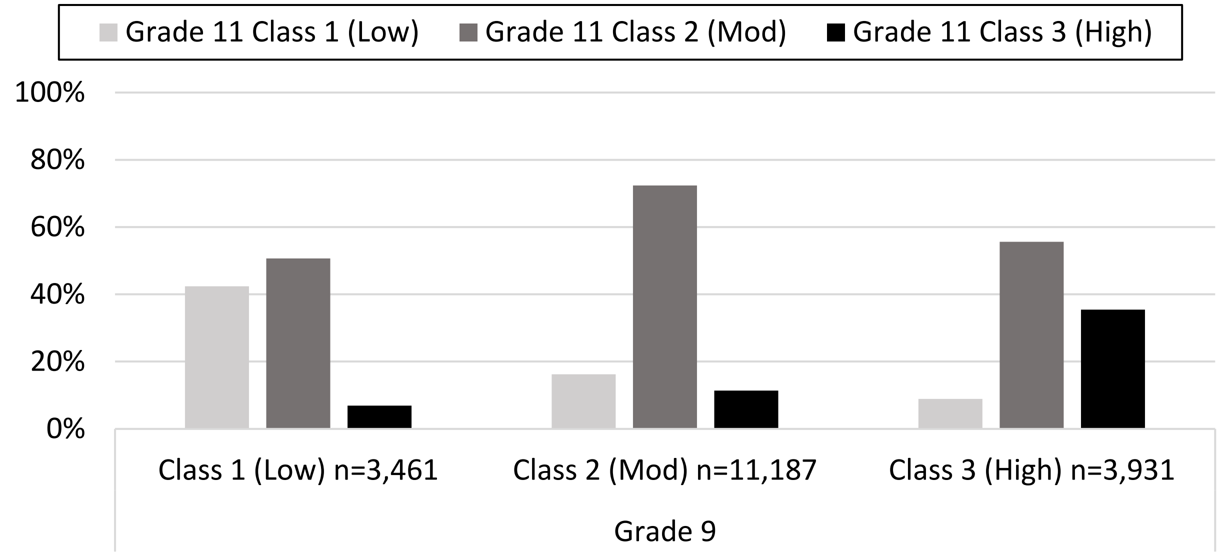


Figure 5. Latent Transition Analysis (Joint) Model-Predicted Within-Class Change from Grade 9 to 11

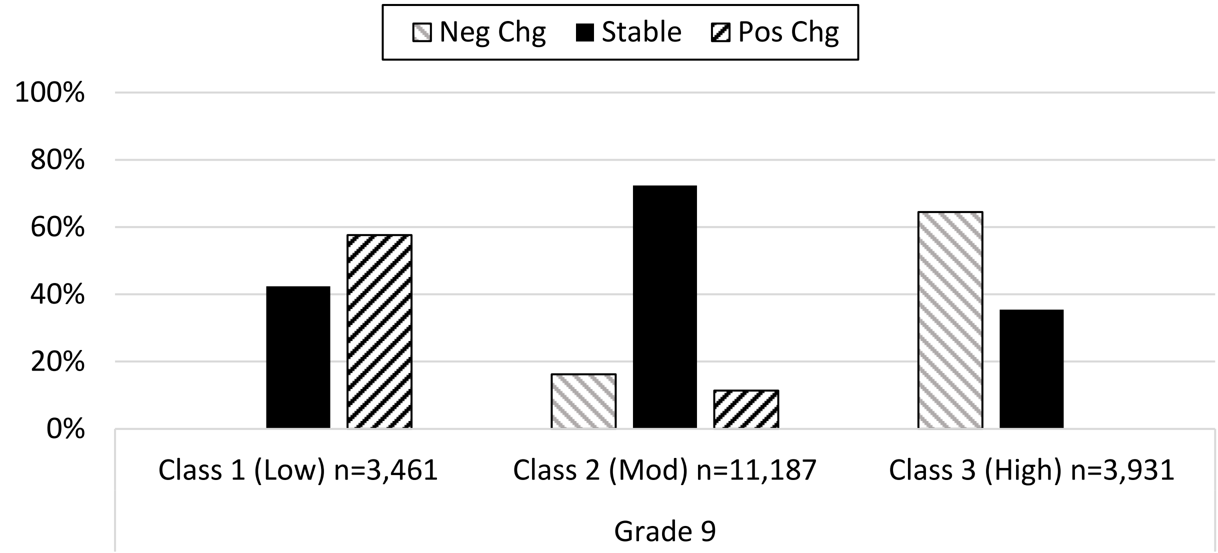


Figure 5. Latent Transition Analysis (Joint) Model-Predicted Within-Class Patterns of Change in Classifications from Grade 9 to 11: “Stayers” vs. “Movers”

Appendix: Example *Mplus* Code for LCA, LTA, and Continuous Latent Variable Models

Grade 9 3-Class LCA
(Variable List Truncated for Brevity)

```
USEVARIABLES ARE Q238 Q239
 Q240 Q244 Q245 Q246 Q247;
 IDVARIABLE IS ID;
 MISSING ARE ALL (-99);
 WEIGHT = Q10;
 CLASSES = c(3);
 ANALYSIS:
 TYPE = MIXTURE;
 DEFINE:
 STANDARDIZE Q238 Q239
 Q240 Q244 Q245 Q246 Q247;
 SAVEDATA:
 FILE = LCA_3class_FINAL_new.txt;
 SAVE = CPROB;
 FORMAT IS FREE;
 OUTPUT:
 TECH1 TECH8 TECH11
 Plot:
 type=plot2;
```

Grade 11 3-Class LCA
(Variable List Truncated for Brevity)

```
USEVARIABLES ARE Q350 Q351
 Q352 Q353 Q354 Q355 Q356;
 IDVARIABLE IS ID;
 MISSING ARE ALL (-99);
 WEIGHT = Q10;
 CLASSES = c(3);
 ANALYSIS:
 TYPE = MIXTURE;
 DEFINE:
 STANDARDIZE Q350 Q351
 Q352 Q353 Q354 Q355 Q356;
 SAVEDATA:
 FILE = LCA_3class_w2_Final_new.txt;
 SAVE = CPROB;
 FORMAT IS FREE;
 OUTPUT:
 TECH1 TECH8 TECH11
 Plot:
 type=plot2;
```

3-Classes per Grade, Two Grades LTA
(Variable List Truncated for Brevity)

```
USEVARIABLES ARE Q239 Q240
 Q238 Q244 Q245 Q246 Q247 Q352 Q355
Q350 Q354 Q351 Q353 Q356;
 IDVARIABLE IS ID;
 MISSING ARE ALL (-99);
 WEIGHT = Q10;
 CLASSES = c1(3) c2(3);
 DEFINE:
 STANDARDIZE Q239 Q240
 Q238 Q244 Q245 Q246 Q247 Q352 Q355
Q350 Q354 Q351 Q353 Q356;
 ANALYSIS:
 TYPE = MIXTURE;
 ALGORITHM = INTEGRATION;
 MODEL:
 %Overall%
 c2 on c1;
 model c1:
 %c1#1%
 [Q239](11);
 [Q240](12);
 [Q238](13);
 [Q244](14);
 [Q245](15);
 [Q246](16);
 [Q247](17);
 %c1#2%
 [Q239](28);
 [Q240](29);
 [Q238](30);
 [Q244](31);
 [Q245](32);
 [Q246](33);
 [Q247](34);
 %c1#3%
 [Q239](45);
 [Q240](46);
 [Q238](47);
 [Q244](48);
 [Q245](49);
 [Q246](50);
 [Q247](51);
 model c2:
 %c2#1%
 [Q352](11);
 [Q355](12);
 [Q350](13);
 [Q354](14);
 [Q351](15);
 [Q353](16);
 [Q356](17);
 %c2#2%
 [Q352](28);
 [Q355](29);
 [Q350](30);
 [Q354](31);
 [Q351](32);
 [Q353](33);
 [Q356](34);
 %c2#3%
 [Q352](45);
 [Q355](46);
 [Q350](47);
 [Q354](48);
 [Q351](49);
 [Q353](50);
 [Q356](51);
 OUTPUT: TECH1 TECH10 TECH14;
 SAVEDATA:
 FILE =
LTA_9_11_standard_metric_nw.txt;
 SAVE = CPROB;
 FORMAT IS FREE;
```

Grade 9 Continuous Motivation Predicting Grade 11 Continuous Motivation (Variable List Truncated for Brevity)

```
USEVARIABLES ARE Q239 Q240 Q238 Q244 Q245 Q246 Q247
 Q352 Q355 Q350 Q354 Q351 Q353 Q356;
 IDVARIABLE IS ID;
 MISSING ARE ALL (-99);
 WEIGHT = Q10;
 DEFINE:
 STANDARDIZE Q239 Q240 Q238 Q244 Q245 Q246 Q247
 Q352 Q355 Q350 Q354 Q351 Q353 Q356;
 ANALYSIS:
 TYPE = GENERAL;
 ESTIMATOR = MLR;
 MODEL:
 gr9 BY Q239 Q240 Q238 Q244 Q245 Q246 Q247;
 gr11 BY Q352 Q355 Q350 Q354 Q351 Q353 Q356;
 gr11 ON gr9;
 SAVEDATA:
 FILE = LV_9_11_standard_metric_nw.txt;
 FORMAT IS FREE;
```