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Middle School Transition: An Application of Latent Transition Analysis (LTA) on easyCBM® Benchmark Mathematics Data

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ABSTRACT

The objective of this study was to explore the elementary to middle school transition in mathematics by evaluating the change in latent class structure and representative proportions. All data came from easyCBM®, an online formative assessment system. Tri-annual benchmark assessments were given to all participants. There were four grades and five cohorts under this current study, counter-balanced in a quasi-experimental design. In each cohort, four measures were used over a two-year span, administered in the fall and spring of 2009-2010 and 2010-2011. Latent transition analysis (LTA) was utilized. Results indicated that a greater proportion of students were in the high mathematics achievement class across four time points in all non-transition cohorts. On the other hand, students dropped in mathematics achievement at least one or two time points for transition cohorts. Students experience a drop in mathematics achievement once they move into middle school.

Keywords: middle school transition, latent transition analysis (LTA)

Introduction

Students making the transition from elementary to middle schools face many changes in their academic environment. They move from self-contained classrooms to a schedule with many transitions during the day. They must acquire a level of autonomy and organization not necessarily needed in elementary school. They also must transition to a school day that is dramatically restructured, including multiple teachers instructing students in one specific subject. Middle schools often serve much larger geographic areas than elementary schools and the building and student population are also generally much larger. The larger school combined with the restructured schedule leads to a reorganization of students' social framework, as students may have different classmates during each class period.

Previous research has found a drop in students' mathematics achievement can happen associated with the middle school transition (e.g., Alspaugh, 1998; Alspaugh & Harting, 1995; Linnenbrink, 2010). Linnenbrink (2010) applied a hierarchical linear regression model to five years of state testing data and found that the drop in achievement was more severe in mathematics than in reading. Alspaugh and Harting (1995) found a consistent drop in mathematics achievement for students who were making a middle school transition versus those who were not, regardless of when the transition occurred (K-4, K-5, K-6, K-7, and K-8 school formats were investigated). Like Linnenbrink (2010), Alspaugh and Harting used five years of historical state testing data in a matched group design, matching the samples by school size and proportion of students eligible for free or reduced price lunch.

Nearly all the research on the effect of middle school transition to date has applied annual statewide testing results as the criterion (e.g., Alspaugh, 1998; Alspaugh & Harting, 1995; Linnenbrink, 2010; Wihry, Coldarci, & Meadow, 1992). However, many of the nuances associated with students' achievement during the middle school transition cannot be parsed out by these 'single shot' measures. For example, a common supposition, first posited by Alspaugh and Harting (1995), is that students eventually ‘recover’ from the effects of the middle school transition (i.e., their achievement levels match those of students who did not experience a school transition). However, by only using one time-point in each year, it is unclear at what point of the school year this recovery begins to occur. Also, the drop and recovery are generally evaluated at the aggregate group mean level, rather than at the individual student level. By evaluating achievement only at the group mean level, particularly for the notions of drop and recovery, it is difficult to understand how the drop and recovery are occurring. For example, perhaps a majority of students recovers and even improves in their academic performance after a given amount of time, while a small group of students never truly recovers from the transition and instead falls further behind. It is likely that these students would be overlooked when viewing the data only at the aggregate mean level.

In order to overcome these potential shortcomings in previous research, we extend this line of research by (a) using multiple time-points within each academic year, and (b) applying sophisticated statistical model that allow us to classify students depending on the pattern of changes in their item response patterns, which may be due to differences in their achievement levels. Similar to Alspaugh and Harting (1995), we investigated school-to-school transitions at multiple grade levels. Our samples of students came from schools in K-5 and K-6 formats. In our analysis, we used two years of assessment data administered twice annually (fall and spring administrations). Furthermore, for each of the K-5 and K-6 school format, we included two cohorts of students – those making a school transition over the two-year span and those staying within the same school. Each cohort making a school transition thus had a comparison group of students who were not making a school transition but still making the same grade transition. Additionally, in order to depart from the group-level mean evaluation, we adopted mixture modeling analysis approaches to investigate the problem.

Dealing with heterogeneous populations is not uncommon in social and behavioral science fields, such as education and psychology. Such heterogeneity is usually due to a mixture of subgroups of individuals that display different patterns of effects in the target population. Many traditional statistical procedures assume homogenous populations, but statistical inferences obtained from these procedures may be misleading if an assumption of a homogeneous population is not reasonable. If the source of heterogeneity is known, subgroups can be identified on the basis of that source alone (e.g., demographic covariates). If, on the other hand, the source of heterogeneity is unknown, then subgroups cannot be defined explicitly. In the case of the latter, the subgroups are referred to as latent classes (e.g., Luke & Muthén, 2005). Latent class analysis (LCA) and latent transition analysis (LTA) are examples of mixture modeling for dealing with a heterogeneous population when the source of heterogeneity is unknown.

Mixture modeling refers to modeling categorical latent variables represented in subgroups. For cross-sectional data, a latent class analysis (LCA) is a special case of mixture modeling, where latent classes explain the relationships among the observed dependent variables, which is similar to a factor analysis (e.g., Muthén & Muthén, 2007). For longitudinal data, an LCA is extended to a latent transition analysis (LTA), in which changes of latent class affiliations over time are evaluated (e.g., Muthén & Muthén, 2007; Nylund, 2007). By using either LCA or LTA, one can identify mutually exclusive latent classes, which account for the distribution of the observable measures within the sample.

LTA is modeled as a type of structural equation model (SEM) comprised of both a measurement and structural model. In fact, LCA is used as the measurement model in LTA to identify unique classes at each point in the analysis. LTA combines cross-sectional measurement of categorical latent variables with a longitudinal description of change in the latent categories over time. Each individual is assigned to the latent class for which they have the highest posterior probability of membership at each time point. Therefore, LTA allows us to evaluate changes in individuals' latent class membership over time.

It has been demonstrated in the literature that LTA is useful in educational research. For example, Cho, Cohen, Kim, and Bottge (2010) demonstrated the use of an LTA model with a mixture Rasch model as the measurement model, using data from an enhanced anchored instruction (EAI) instructional treatment fraction of the cost (FOC) math test. They used a sample of 109 seventh grade students with and without an identified learning disability across three time points and found that all students with learning disability transitioned into a high-ability latent class following the FOC instruction. On the other hand, Dembo, Wareham, Poythress, Meyers, and Schmeidler (2008) studied antisocial behavior risk factors among 137 youths by applying LTA across two time points. Their LTA results revealed that about two thirds of the youths did not transitioned from the at-risk latent class to the non-risk latent class. In sum, LTA is a useful and appropriate data analysis technique, when our interest is to evaluate how individuals' latent class memberships change over time.

LTA allows for an examination of an individual's most likely latent class pattern over time. Assuming two classes are identified for each of four time points, an LTA would provide the counts and proportions for 16 latent class patterns ($2\times2\times2\times2=16$). If there are three classes for each of four time points, LTA would provide 81 latent class patterns ($3\times3\times3\times3=81$). Each latent class pattern has its own meaning. For example, assume we have a two-class model across four time points, and we have identified the latent class 1 as "high achievement student", and latent class 2 as "low achievement student". If a student is found to be most likely to be in latent class 1 for all four time points, this student would be assigned into Latent Class Pattern 1111. Note that the first '1' in Latent Class Pattern 1111 represents the assigned class for the first time point, whereas the second, third, and fourth '1s' represent the assigned class for the second, third, and fourth time points, respectively. We would interpret that this particular student stayed in the high achievement class across all time points. On the other hand, if a student's latent class pattern was 1212, the interpretation would be quite different, because the student 'bounces' between the high achievement class and the low achievement class. In other words, we would interpret that this student stayed in the high achievement class for the first time point, he/she moved into the low achievement class at the second time point. Then, this student moved back to the high achievement class for the third time point. This student moved into the low achievement class again in the fourth time point. We could then begin to look for explanations why this particular pattern occurred. These individual progression latent class patterns provide important information about how the individual students are changing over time and how individuals with specific response patterns differ from each other.

A growth mixture modeling (GMM) is another mixture modeling approach potentially useful for our research purpose. A GMM classifies individuals into latent classes by evaluating all investigated time points at once, whereas LTA classifies individuals into latent classes separately at each time point. Although a GMM can classify individuals into latent classes, it focuses on describing between-class differences in their patterns of changes over time in terms of the shapes of the fitted growth curves. On the other hand, an LTA focuses on classification of individuals at each time point and summarizes patterns of classifications over time. More critically, a GMM over a period of two grade levels needs outcome measures that have a common scale across two consecutive grade levels. However, easyCBM scores are comparable only within the same grade level. For these reason, we determined that an LTA fits better for our research purpose than a GMM. In this study, we extend the current literature on middle school transition research by applying longitudinal LTA model. In other words, rather than monitoring students observed change in achievement (i.e., growth), we examine the change in the latent class patterns and their proportions in math achievement data as students move from elementary to middle schools.

Methods

Design: In the United States, many school districts are organized in the elementary school, middle school, and high school model. However, the time at which students enter middle school is not always consistent. In this study, schools were included in two separate models – those with students' entering middle school at grade 6, and those with students' entering middle school at grade 7. We were primarily interested in whether this difference in middle school transition timing was related to latent class transition patterns.

Two years of data were analyzed. The data were collected for each of five different student cohorts in a counter-balanced design with four grade levels. The design is outlined in Table 1. The counter-balanced design was possible because of differing local policies on the middle-school transition. The first two cohorts of students moved from grade 5 to grade 6. In cohort 1, students *did not* make the middle school transition. This cohort was referred to as 5/6NT in this study (NT = no transition). On the other hand, students *made* the middle school transition in cohort 2. This cohort was referred to as 5/6T (T = transition). For the third and fourth cohorts, students moved from grade 6 to grade 7. Again, 6/7NT and 6/7T with students not making and making the middle school transition, respectively. However, while students in the NT in cohort 1 stayed in elementary school for both grades, students in the NT in cohort 3 stayed in middle school for both grades. The fifth cohort moved from grade 7 to grade 8, in which all students stayed in middle school for both grades. The NT cohort served as a pseudo-control group for the T cohort. Cohort 5 served as a comparison group, as it only had a NT cohort. Four school districts participated in this study, with schools in two districts structured in a K-5 format and schools in two districts structured in a K-6 format.

INSERT TABLE1 HERE

Measure: Item response patterns from the easyCBM® mathematics measures were used for all analyses. The easyCBM® is an online comprehensive benchmark and progress monitoring assessment system designed for use within a response to intervention (RTI) framework. The full assessment system contains measures in reading and mathematics in K-8 grade levels. The easyCBM® mathematics measures for grades 5-8 are used in this current study. For most districts, the easyCBM® benchmark mathematics tests are administered seasonally: fall, winter, and spring. However, only measures from fall and spring in each year were used in this study, because of unavailability of winter measure data in one of the participating districts. The easyCBM® mathematics benchmarks contain 45 items for each measure aligned to the National Council of Teachers of Mathematics (NCTM) focal point standards. All items contained three response options; a correct response, one near distractor, and one far distractor. Student performance is reported as a summed raw score.

Sample: Samples included students from four school districts in the Pacific Northwest. For the purpose of this study, only students who were present for all four testing occasions across the two years of the study in each condition were included in the analysis. The full sample sizes ranged from 2,278 to 4,259 for the five cohorts. Table 2 presents the sample size, Cronbach's alpha reliability coefficients of each measure, and student demographics in each cohort. The actual sample sizes ranged from 716 to 1,715 for the five cohorts by using the listwise detection. The Cronbach's alpha reliability coefficients were above .84 across measures across cohorts. Approximately

65% of students in the sample were white, 50% were female, and less than 10% were English Language Learners (ELL). Approximately 27% of students in the sample were eligible for free or reduced price lunch (FRL), and approximately 12% of students received special education services (SPED).

INSERT TABLE2 HERE

Analysis: Although the measures had been verified by the easyCBM© system (e.g., Alonzo, Anderson, & Tindal, 2009), a unidimensional Rasch model was fit to the measures as preliminary analyses to re-confirm the quality of the measures by evaluating item difficulties. Results of a total of 20 Rasch analyses (2 measures per year×2 years of data×5 cohorts) indicated all item difficulties were within an acceptable range. After evaluating item difficulties, we conducted 5 LTA analyses: one for each cohort. Each LTA analysis included four time points with 45 test items in each time point, totaling 180 items per analysis. We explored the number of latent classes by using three information criteria: Akaike information criterion (AIC), Bayesian information criterion (BIC), and Adjusted Bayesian information criterion (ABIC). Smaller value indicates better fit. All parameters were estimated with the M*plus* software using the Maximum Likelihood estimator with robust standard errors. The class labeling in M*plus* is arbitrary. In our analyses, the class with lower item difficulties was labeled as Latent Class 1 before tabulating results for consistency.

Results

It was revealed that the two-class LTA model fit the data best across five cohorts (see Table 3). The results of the two-class LTA model are reported here. The mean item difficulties were similar for the five cohorts within the same latent class pattern (see Table 4). When mean item difficulties were compared between Latent Class Patterns, the Latent Class Pattern 1111 showed the lowest mean item difficulty values, whereas the Latent Class Pattern 2222 showed the highest mean item difficulty values. Latent Class 1 represented a group of students with “high mathematics achievement”, whereas Latent Class 2 represented a group of students with “low mathematics achievement”.

Table 5 displays Latent Class 1 proportions of individuals based on their most likely latent class membership for the two-class LTA model and entropy values. An entropy value is an index of classification quality, which is evaluated by the consistency of class proportions between estimated parameters of class proportions and observed class proportions based on estimated highest class probabilities of individual observations. The entropy can range from 0.0 to 1.0, and a value close to 1.0 indicates a good classification quality. For our analyses, the entropy was above .96 for all five LTA analyses, indicating very good classification qualities. The proportion of students in Latent Class 1 was higher than .50 across four time points for all NT cohorts. For cohort 5/6NT, Latent Class 1 proportions were .787, .635, .641, and .596 for the four time points, respectively. For this cohort, the Latent Class 1 proportion did not drop in the second year. On the other hand, the Latent Class 1 proportions dropped in their second years for cohorts 6/7NT and 7/8NT. The Latent Class 1 proportions increased in their spring measure of the second year, but not to the levels they were in the first year (.578, .705, .556, and .635 for cohort 6/7NT, and .636, .652, .527, and .573 for cohort 7/8NT). For students in the 5/6T cohort, the Latent Class 1 proportions were .560, .447, .297, and .651 for the four time points. It appeared that the drop in the fall of the transition year of grade 6 was substantial (from .447 to .297), but a substantial recovery occurred by the end of the transition year (from .297 to .651). For another middle school transition cohort (6/7T), the proportion of students in Latent Class 1 were .595, .693, .459, and .553, where a more substantial drop of the Latent Class 1 proportion happened at the beginning of grade 7. However, a substantial recovery did not happen for this cohort (from .459 to .553). In sum, Latent Class 1 was larger than Latent Class 2 across four time points on the three NT cohorts. In other words, a greater proportion of students were in the high mathematics achievement class in all the non-transition cohorts than in the transition cohorts. On the other hand, Latent Class 1 was smaller than Latent Class 2 on time point 2 for cohort 5/6T and time point 3 for cohort 6/7T.

Table 6 displays the proportion of individual classifications based on their most likely latent class pattern. Overall, the three most frequently latent class patterns across cohorts were 1121, 1111, and 1122. Many students were classified into high mathematics achievement class across four time points in over the two years (Latent Class Pattern 1111). Some students dropped in mathematics achievement at the beginning of the second year but recovered by the end of the year (Latent Class Pattern 1121). Other students did not recover by the end of the second year (Latent Class Pattern 1122). Approximately 47%, 34%, 31%, 51%, and 38% of all students were classified into one of these three patterns for cohorts 5/6NT, 5/6T, 6/7NT, 6/7T, and 7/8NT, respectively.

There were consistently higher percentage of students classified to Latent Class Pattern 1111 for students in the NT cohorts than students in the T cohorts (14%, 18%, 12%, and 15% for 5/6NT, 6/7NT, 7/8NT, and 6/7T, respectively). In contrast, only 1% of students in the 5/6T cohort were classified to this pattern. It is interpreted that students entering middle school at grade 6 had a hard time to maintain their mathematics achievement across two years than students who entering middle school at grade 7 (1% for 5/6T vs. 15% for 6/7T). On the other hand, a higher percentage of students were classified to Latent Class Patterns 1121 and 1122 for the T cohorts rather than the NT cohorts indicated that students dropped in their mathematics achievement once they moved to middle school. For 5/6NT and 6/7NT cohorts, approximately 18% and 11% of students were classified to Latent Class Pattern 1121. In contrast, 21% (5/6T condition) and 19% (6/7T condition) were classified to this pattern, and approximately 16% of students were classified to this pattern in the 7/8NT condition. Regarding Latent Class Pattern 1122, approximately 16% and 2% of students were classified to this pattern for 5/6 NT and 6/7NT cohorts. On the other hand, 12% and 18% of the students were classified to this pattern for the 5/6T and 6/7T cohorts. Approximately 11% of students were classified to this latent class pattern for the 7/8NT cohort. In summary, for 5/6 grade students, the middle school transition effect is shown as the difference in Latent Class Pattern 1111, whereas for 6/7 grade students, the middle school transition effect is shown as the difference in Latent Class Patterns 1121 and 1122.

INSERT TABLES 3, 4, 5, and 6 HERE

Conclusions and Discussions

This study investigated the change of students' achievement overtime by a mixture modeling perspective, in relation to the middle school transition. Our study demonstrated that the LTA was able to capture middle school transition effect. Overall, results confirm the existence of middle school transition effect. Moreover, our results align with previous literature showing a drop in mathematics performance coinciding with the transition to middle school (e.g., Alspaugh, 1998; Alspaugh & Harting, 1995; Linnenbrink, 2010). Perhaps most importantly, our analyses of four time points across two years allowed us to examine not only the drop in mathematics achievement but also (a) whether the drop in achievement occurs immediately with the middle school transition (e.g., Latent Class Patterns 1121 or 1122) or if there is a delayed effect (e.g., Latent Class Pattern 1112) and (b) if there is a recovery period, and when that recovery may occur (e.g., Latent Class Pattern 1121).

There are three separate latent class patterns that align with the middle school transition achievement drop; 1112, 1122, and 1121. Latent Class Pattern 1112 represents students who were classified to the high mathematics achievement class across the first three time points, but dropped in mathematics achievement by the end of the second year. Latent Class Pattern 1122 represents students who were classified to the high mathematics achievement class for the entirety of the first year, but classified to the low mathematics achievement class for the entirety of the second year. Latent Class Pattern 1121 represents students who were classified to the high mathematics achievement class for the entire first year, but a drop in fall of the second year, coinciding with the middle school transition for students in 5/6T and 6/7T conditions. These students, however, recovered by the end of the second year.

Latent Class Pattern 1112, can be interpreted that there was a delayed effect of the middle school transition for students in the T cohorts. For these T cohorts, due to transition to middle school, students were able to maintain their previous level of performance initially, but the rigors of middle school life eventually weighed on the student and a drop in achievement may have become evident by the end of the year. When examining Table 7, it does not appear that students in the transition cohorts were classified to this latent class pattern at a higher rate than students in the other latent class patterns. There was not a delayed middle school transition effect for these particular samples. Therefore, the transition to middle school did not play a large role in whether or not students' achievement follows Latent Class Pattern 1112.

Latent Class Pattern 1122, would suggest the middle school transition had an immediate and lasting effect, with the student unable to recover by the end of the year. However, students with Latent Class Pattern 1122 may still recover in the following year. In grades 5/6, the proportions of students who were classified to this pattern between the transition and the no-transition cohorts were slightly different (12% vs. 16%). One interpretation is that many students in grades 5/6 experienced drop in mathematics achievement, but their drops are likely associated with changes other than middle school transition. In contrast, students in grades 6/7 were classified to this latent class pattern at a much higher rate for the transition cohort (18%) than the no-transition cohort (2%). This finding demonstrates a significant role on middle school transition effect. It is suspected that the middle school transition effect had a larger effect on students who entered middle school at grade 7 than who entered middle school at grade 6.

Finally, Latent Class Pattern 1121 suggested that there was an immediate drop in the second year, but the recovery began *during* the second year. In this pattern, Latent Class 1 proportions were roughly the same before the second year. For both grades 5/6 and 6/7 students were classified to this pattern at a higher rate if they made the middle school transition, but particularly for students in grade 6/7. This again demonstrates a potentially stronger middle school transition effect for a transition at grade 7 than for a transition at grade 6. Also, while Alspaugh and Harting (1995) found that students generally recovered during the year following the middle school transition year. This study provides evidence that the recovery may actually begin *during* the transition year.

The middle school transition is a difficult time for students as they face many changes in their lives. The results of our study, combined with previous work (e.g., Alspaugh & Harting, 1995; Feldlaufer, Midgley, & Eccles, 1989; Linnenbrink, 2010), suggest that a precipitous drop in achievement occurs with the middle school transition. While our work provides new insight into when both the initial drop in performance occurs and when the recovery begins, it has limitations. First, two years of data were used in this study. Although we are confident in our design with two years of data across four grades, and five cohorts, more years of data would have been desirable. However, an extra year of data would have further increased our understanding of the idea that a recovery occurs.

Second, although we examined student demographics in each cohort, covariates that may be related to latent class classifications were not included in the models. Such covariates may further facilitate our understanding of how different student groups make middle school transitions and how they change in their classifications. Therefore, adding covariates that explain classifications should be considered in future research. Third, it was quite time-consuming to fit our LTA model to our data. We used a quad-core 4.0 GHz Intel Core i7 processor with 24 GB of memory, yet it took about 42 hours to complete one LTA analysis.

Finally, this study explored elementary schools structured in K-5 and K-6 formats, but a contingent of schools in the United States are moving toward a K-8 format (e.g., Pardini, 2002), eliminating middle schools. It would be interesting for future studies to include a set of schools organized in the K-8 format. The results could then be used to further explain whether the drop in achievement is truly a 'middle school' effect. Interestingly, however, many schools organized in a K-8 format function like a traditional middle school in the upper grades (e.g., subject specific teachers, and multiple transitions) (e.g., Clinton, 2011). Thus, if the drop in achievement were not observed in these schools it would lend evidence to the drop in achievement being largely due to the change in building and social environment, but perhaps not due to changes in the daily environment. Future studies should investigate these and other issues around the middle school transition to help us better understand the optimal learning environment for students in 6-8 grade levels.

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Table 1

The Structure of Five Cohorts

Cohort	Matriculation Pattern	Grade			
		5	6	7	8
1	5/6NT	Elementary	Elementary	---	---
2	5/6T	Elementary	Middle school	---	---
3	6/7NT	---	Middle school	Middle school	---
4	6/7T	---	Elementary	Middle school	---
5	7/8NT	---	---	Middle school	Middle school

Note. NT = no transition; T = Transition

Table 2

Sample size, Cronbach's Alpha Reliability Coefficient, and Percentage of Student Demographic in each Cohort

		Reliability				Student Demographic				
Cohort	*n*	Fall 2009	Spring 2010	Fall 2010	Spring 2011	White	Female	ELL	FRL	SPED
5/6NT	1,229	.858	.913	.872	.910	57.7	47.7	9.0	10.8	12.2
5/6T	1,465	.844	.889	.847	.900	73.3	51.0	2.9	47.9	16.7
6/7NT	716	.843	.899	.869	.887	72.5	54.2	2.9	47.1	15.2
6/7T	1,211	.857	.906	.900	.911	59.3	49.2	6.8	9.2	10.0
7/8NT	1,715	.882	.902	.885	.895	63.6	49.1	5.2	23.6	12.0

Note. FRL = student eligible for free or reduced price lunch.

Table 3

Fit Indices of the LTA Model

		Model Selection Criteria		
Cohort	Number of Class	AIC	BIC	ABIC
5/6NT	2	178909.194	193673.186	184502.839
	3	179134.200	195599.570	184610.515
5/6T	2	220800.207	236071.313	226900.210
	3	221194.501	244675.856	231386.777
6/7NT	2	124567.641	137771.855	128604.867
	3	125289.713	141705.918	129416.969
6/7T	2	185265.060	199986.455	190816.178
	3	185438.547	199992.574	192613.521
7/8NT	2	306292.759	322018.734	312847.057
	3	310354.265	331849.958	315605.861

Table 4

Mean Item Difficulty in each Latent Class Pattern by the Two-class LTA Model

	Mean Item Difficulty				
Pattern	5/6NT	5/6T	6/7NT	6/7T	7/8NT
1111	-3.369	-3.107	-2.653	-3.056	-2.988
1112	-1.891	-1.821	-1.825	-1.532	-1.374
1121	-2.488	-2.561	-2.061	-2.412	-2.122
1122	-1.951	-1.305	-1.326	-1.708	-1.224
1211	-1.312	-1.135	-1.499	-0.878	-1.023
1212	-0.985	-0.832	-0.922	-0.669	-0.800
1221	-1.264	-0.748	-1.109	-0.570	-0.628
1222	-0.791	-0.489	-0.758	-0.855	-0.261
2111	-0.866	-1.532	-0.651	-0.699	-0.641
2112	-0.234	-0.628	-0.282	-0.192	-0.376
2121	-0.554	-0.945	-0.308	-0.155	-0.319
2122	-0.199	-0.576	-0.104	-0.286	-0.226
2211	0.052	-0.811	0.243	0.047	0.016
2212	0.058	-0.337	0.261	0.187	0.167
2221	0.142	0.238	0.209	0.207	0.442
2222	0.350	0.232	0.461	0.542	0.561

Table 5

Class Proportion of Individuals based on Their Most likely Latent Class Membership and Entropy by the Two-class LTA Model

Cohort	Latent Class 1 Proportion								Entropy
	G5 Fall	G5 Spring	G6 Fall	G6 Spring	G7 Fall	G7 Spring	G8 Fall	G8 Spring	
5/6NT	.787	.635	.641	.596	---	---	---	---	.964
5/6T	.560	.447	.297	.651	---	---	---	---	.967
6/7NT	---	---	.578	.705	.556	.635	---	---	.987
6/7T	---	---	.595	.693	.459	.553	---	---	.972
7/8NT	---	---	---	---	.636	.652	.527	.573	.965

Table 6

Proportion of Classification of Individuals based on Their Most likely Latent Class Pattern by the Two-class LTA Model

Pattern	Proportion				
	5/6NT	5/6T	6/7NT	6/7T	7/8NT
Dominant pattern					
1111	.138	.010	.180	.145	.115
1121	.179	.205	.113	.190	.164
1122	.155	.123	.018	.176	.105
Non-dominant pattern					
1112	.068	.029	.106	.097	.077
1211	.068	.064	.004	.043	.056
1212	.022	.049	.027	.015	.037
1221	.083	.204	.096	.050	.042
1222	.073	.041	.056	.080	.040
2111	.028	.038	.161	.031	.049
2112	.005	.024	.047	.007	.033
2121	.024	.044	.011	.021	.058
2122	.037	.034	.046	.027	.051
2211	.025	.044	.014	.017	.052
2212	.005	.020	.010	.005	.054
2221	.052	.041	.059	.057	.036
2222	.037	.030	.052	.040	.030