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Stability and Instability of Peer Victimization during Middle School: Using Latent Transition Analysis with Covariates, Distal Outcomes, and Modeling Extensions

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Abstract

This paper is an advanced application of latent transition analysis (LTA). Examining the peer victimization experiences of approximately 1300 urban, public school students across the 3 middle school years, we extend the conventional LTA model to simultaneously include time varying covariates with time varying effects, second-order effects, a mover-stayer variable, and distal outcomes. We present five key modeling steps that can be used in the application of the LTA model. The analyses yielded three victim classes based on victimization degree (victimized, sometimes victimized, nonvictimized). LTA indicated that when students transitioned between victimization classes, they were most likely to transition from a more victimized group into one of the less victimized groups. Further, results indicated that students who experience any sort of victimization, compared to those who do not, felt less safe at school, more socially anxious, and more depressed during certain middle school years. We also found that students who were chronically victimized in middle school reported more physical health problems and more social worries once in high school.

Stability and Instability of Peer Victimization during Middle School: Using Latent Transition Analysis with Covariates, Distal Outcomes, and Modeling Extensions

Peer victimization is a known antecedent of a wide range of negative outcomes for youth, from psychological and social maladjustment to physical symptoms to problems in school functioning (Juvonen & Graham, 2001). Around sixth grade, peer victimization appears to reach its peak in frequency (Nansel et al., 2001), but the research pointing to this peak has been mainly cross sectional (e.g., Salmivalli, 2002). Less is known about what happens longitudinally and it is likely that peer victimization does not decrease for all youth. At the same time, while a host of research has identified antecedents, covariates, and consequences of peer victimization (Juvonen & Graham, 2001; Hawker & Boulton, 2000), less is known about the covariates (especially time varying covariates) that might predict victimization over time. There is also limited research about the extended consequences associated with different patterns of peer victimization (cf., chronically victimized, consistently nonvictimized) (Juvonen, Nishina, & Graham, 2000).

The wider availability of different longitudinal models allows researchers to describe change and integrate important correlates and consequences of change into the models to understand development more completely. The present study outlines five important modeling steps for using latent transition analysis (LTA)—including key model extensions—to demonstrate the types developmental processes LTA can identify. Time invariant and time varying covariates, distal outcomes, and a mover-stayer second-order latent variable are explored in relation to peer victimization during early adolescence. A second-order transition effect is also used to describe longitudinal transitions into and out of peer victimization classes.

The most common longitudinal models are the growth curve and the auto regressive models (Collins & Sayer, 2001). These models differ in the research questions they address. A growth model describes the general rate at which peer victimization changes during middle school, while an autoregressive model describes the probability of a student transitioning from one victimization state to another between grades. In growth modeling, dependent variables are correlated through the growth parameters while in autoregressive models the dependent variables are directly related to each other. In autoregressive models, change parameters are regression coefficients that describe the relationship between adjacent time points, implying that victim status from earlier school years directly affects status in later school years. For example, students' peer victimization status in sixth grade should predict their victimization status in seventh grade. The latent variable can represent a continuous factor or a categorical latent variable.

The Latent Transition Analysis Model

This paper describes one specific type of autoregressive model, the latent transition analysis (LTA) model, originally introduced by Graham, Collins, Wugalter, Chung, and Hansen (1991; for a technical description see Chung, Park, & Lanza, 2005; Humphreys & Janson, 2000; Reboussin, Reboussin, Liang, & Anthony, 1998). LTA is particularly suited to modeling change in group membership over time (e.g., movement between the victimized, sometimes victimized, and nonvictimized groups). Key features of LTA models distinguish them from other autoregressive models. Specifically, in LTA, groups of interest (sometimes called states, statuses, or latent classes), are not directly observed (i.e., they are latent) and they are identified with a measurement model. As a result, LTA involves a measurement component that captures the latent groups (e.g., victimization status), and a structural component that models change among the groups over time. LTA has been used when testing different psychological theories based on stage development, for example, where the discrete groups represent reading development states

(Collins, 2006), children's drawing abilities (Humphreys & Janson, 2000), and pubertal timing and its relationship with substance abuse (Chung et al, 2005).

The flexibility of the LTA model allows for the integration of developmental theories directly into the statistical model. For example, in addition to modeling year to year change in victimization status, we can also add a second-order transition effect to test whether there is a longer lasting impact of earlier victimization status on later victimization. Additionally, there can be differential movement among the latent states, for example, exploring whether transitions among the victimization classes are different between sixth and seventh compared to seventh and eighth grades (e.g., whether the decrease in victimization happens early or late for most students).

LTA model parameters. There are several LTA model parameters of interest that relate to the measurement and structural models. The measurement parameters of an LTA model with LCA are the item probabilities, which are class specific parameters that describe the probability of an individual in given class to endorse each item (e.g., the likelihood of a student in the victimized class endorsing the "gets called bad names" item).

The structural parameters of the LTA model describe the size of each class and movement among them. Class probabilities are parameters describing the relative size of each of the classes. Transition probabilities for a lag-1 LTA are conditional probabilities that describe the probability of being in a given state, conditional on the state from the previous time point (e.g., a student classified as sometimes victimized, conditional on their victimization class the previous year). Transition probabilities of a lag-1 model are estimated using the following equation:

$$\tau_{ikm} = \frac{\exp(\alpha_m + \beta_{km})}{\sum_{s=1}^{S} \exp(\alpha_s + \beta_{ks})}$$

which is the probability of individual *i* transitioning into state *m* $(m = 1, \ldots, S)$ at time point *t*, from state *k* (k = 1, . . ., S) at time point $t - 1$, where the term in the denominator for the last class (i.e., the reference class) is 1 because $\alpha_S = 0$ and $\beta_{kS} = 0$ for standardization (Reboussin et. al., 1998). Transition probabilities are displayed in a transition table. Most applications of LTA are limited to first-order (lag-1) models (i.e., status at time *t* is dependent only on the status at time $t - 1$, not the status at time $t - 2$). This restriction, typically due to software limitations, may not fit the data well and can be relaxed.

Covariates and distal outcomes are important additions to the model because they describe heterogeneity in transitions and help to describe differences in developmental trajectories of victimization. Covariates can identify whether, for example, gender or maladjustment predicts whether students will move to less victimized groups. Existing research consistently implicates a variety of psychosocial correlates of victimization during adolescence, including depressive symptoms, social anxiety, and feeling unsafe in school (Graham, Bellmore & Mize, 2006; Nishina, Juvonen, & Witkow, 2005; Ozer &Weinstein, 2004). However, whether these psychosocial factors predict movement between different victimized states is not known.

Within the LTA framework, distal outcomes can be included to identify the consequences of different developmental trajectories. For example, does movement from a victimized to a nonvictimized state across grades predict better subsequent adjustment (cf., remaining chronically classified as a victim)? To date, longitudinal models applied to understanding victimization during early adolescence have mainly focused on processes by which peer victimization predicts subsequent maladjustment (e.g., Troop-Gordon & Ladd, 2005) but little research has examined how adolescents' victimization classification across time (i.e., classified as a chronic victim or not) predicts later adjustment (see Juvonen, Nishina, & Graham, 2000).

The Present Study

The present study used LTA to model change in student's self-reported peer victimization in a large sample of middle school students across the spring of 6th, 7th and 8th grades. Our starting point was the Nylund, Bellmore, Nishina, & Graham (2006) paper which used latent class analysis (LCA) to empirically identify three distinct classes of students based on victimization experiences: those with a high probability of endorsing all types of victimization (victimized class), those with a 50/50 probability of endorsing the victimization experiences (sometimes victimized class), and those with a very low probability of endorsing each of the victimization items (nonvictimized class). The three classes were valid and structurally stable (i.e., the same three classes during each semester) across the middle school years.

In this paper, we used LTA to study transitions and transition patterns among these victimization classes throughout the middle school years. This approach enabled us to explore several important questions about the development of victimization and how it relates to key psychosocial variables such as depressive symptoms, social anxiety, perceived school safety, physical symptoms, and social worries. First, while several cross-sectional studies suggest the students experience the most victimization early in middle school (e.g., Nansel et al., 2001), we assessed this longitudinally. We also tested whether students' earlier victimization status predicted later victimization status (i.e., are there lasting effects of 6th grade victimization status on 8th grade status?). Third, to explore whether the timing of one's victim status is important, we examined whether psychological maladjustment was differentially associated with victim class membership in grades 6, 7, and 8. Finally, we sought to identify how many students remain chronically victimized throughout middle school and whether such students carry the negative impact of this experience across the transition into high school.

Method

Participants

The participants used in this study come from a larger longitudinal study examining peer relations, adjustment, and academic performance in middle school, the transition from middle to high school, and factors related to on-time high school graduation. Students were recruited from 1 of 11 low SES public middle schools in the greater Los Angeles, CA area. The sample was ethnically diverse (48% Latino, 17% African American, 12% Asian, 12% Caucasian, 11% multiethnic based on student's self-reports) and was evenly split by gender (56% girls). The participation rates ranged between 99% and 75% for Waves 1 (Fall of 6th grade) and 6 (Spring of 8th grade) of the larger study, respectively[1]. Students were re-recruited during the fall of 9th grade to take part in a new portion of the study exploring the transition to high school. The analysis sample size was 1266 for the final model that included covariates and distal outcomes.

Procedure

Both written parental consent and student assent were obtained in sixth grade (75% response rate; 89% of those received consent). In fall and spring of each middle school semester, students completed self-report measures that included peer victimization and other measures of social, psychological, and academic functioning. In sixth grade, the classroom received $5 for each completed survey; in subsequent years, individual students received $5 each time they completed a survey during middle school and $10 during high school.

Measures

Victimization. Each semester, students completed a 6-item modified version of Neary and Joseph's (1994) Peer Victimization Scale. Designed to be embedded in Harter's (1987) Self-Perception Profile for Children in order to reduce social desirability biases, each item describes two types of individuals: "Some kids are not called bad names by other kids, BUT, Other kids are often called bad names by others kids." For each item, students were asked to circle which type of kid was most like them and then indicate whether it was "sort of true for me" or "really true for me." The original scale has 2 items that reflect general victimization ("picked on" and "laughed at"), 1 item that assesses verbal victimization ("called bad names"), and 1 item that assesses physical victimization ("hit and pushed around"). One added item reflected relational victimization ("gossiped about") and another reflected property damage/theft ("gets their things taken or messed up"), a form of victimization relevant to large urban schools.

For the present study, items were dichotomized such that 0 reflects not endorsing the item (i.e., more like the type of kid who does not get picked on) and 1 reflects endorsing the item (i.e., more like the type of kid who does get picked on). The dichotomized responses made conceptual and practical sense, keeping in mind the extensive longitudinal analysis that they will be used to explore (see Nylund et al., 2006 for more details).

Demographic characteristics. Students self-reported their gender and their ethnicity (i.e., they selected 1 of 10 ethnic categories or provided an open-ended description of their ethnicity). Student ethnicity was aggregated into five primary ethnic categories—Latina/o, African American, Asian, Caucasian, and multiethnic. Preliminary analyses revealed that about 40% of students changed their self-reported ethnic identification at least once during middle school (Nishina, Bellmore, Witkow, & Nylund, 2006). Thus, students' most frequently reported ethnic group (i.e., from sixth through tenth grades) was used. Ethnicity was included in the model using dummy coding, where Caucasian students were coded as the reference group.

Depressive symptoms were measured using the 10-item short form of the Children's Depression Inventory (Kovacs, 1992). Students choose one of three sentences that best describes how they have felt in the past 2 weeks. For example: 0 (*I do most things okay*), 1 (*I do many things wrong*), 2 (*I do everything wrong*). The mean of the 10 items was calculated, with higher scores indicating more depressive symptoms.

Social anxiety was measured using 9 of 12 items from the fear of negative evaluation (e.g., “I worry about what others think of me”) and social avoidance and distress (I’m quiet when I’m with a group of people”) subscales of the Social Anxiety Scale for Adolescents (La Greca & Lopez, 1998). Three items were removed to avoid construct overlap with peer victimization. Responses ranged from 1 (*never true*) to 5 (*always true*) and a mean was computed with higher scores indicating higher levels social anxiety.

School safety. Perceptions of school safety were measured using a 10-item subscale of the Effective School Battery (Gottfredson, 1984). Items tapped general perceptions of safety at school and on the way to school (e.g., “How often do you feel safe while in your school building?”) and were rated from 1, *never*, to 5, *always*. A mean of the items was calculated, such that higher scores reflect stronger perceptions of school safety.

High school physical symptoms were assessed with a list of 12 symptoms (modified from Resnick et al., 1997; Udry & Bearman, 1998), for example “headaches,” “sore throat/coughs.” Students indicated how often they had experienced each symptom in the previous two weeks (1 = *not at all*; 4 = *almost every day*) with higher means reflecting more physical symptoms.

High school social worries were measured using a modified four-item version of the High School Performance Scale (Nukulkij, Whitcomb, Bellmore & Cillessen, 1999). Rated on a 5- point scale (1 = *never;* 5 = *all the time*), items tapped students’ worries about their high school social experiences (e.g., “Now that I am in high school, I worry that I won’t have any friends.”). Higher mean scores reflect more worries about social problems in school.

Data Analytic Strategy

The LTA model used in this study is specified using five(plus) modeling steps that are described in detail in the results section to provide useful guidelines for the application of advanced longitudinal models (we note that Steps 1-2 are presented in detail in the context of an earlier paper, Nylund et al., 2006). As in any data analysis endeavor, a careful application of the methods helps to ensure that model specifications are done in a fashion which does not violate substantive theory and also allows developmental theory to be integrated into the model.

Models were estimated with the latent variable software M*plus*, Version 4.2 (Muthén & Muthén, 2006) using full information maximum likelihood estimation. This approach allows for missing data under missing at random (MAR, see Little & Rubin, 1990; Rubin, 1987) assumptions, where students who have data on at least one variable are included in the analysis, unless they are missing data on the covariates. Standard errors were adjusted using a sandwich estimator to account for the clustered nature of data (students were nested within 11 schools[2]). The LTA models are considered longitudinal mixture models and as with all mixture models are known to converge on local, rather than global solutions (McLachlan & Peel, 2000). The use of random start values ensures that the results are global ones. Annotated M*plus* syntax for the models tested in each of the steps is presented in the appendices.

Determining model fit. With LTA class models, as with many latent variable models, there is not a single statistical indicator of model fit. A combination of statistical indicators and substantive theory are used to decide on the best fitting model. Of the statistical indices, the Bayesian Information Criterion (BIC; Schwartz, 1978) is commonly used and trusted for model comparison, where lower values of the BIC indicate a better fitting model. For cross-sectional LCA measurement models that differ in the number of classes, a bootstrap likelihood ratio test

(BLRT) is used to determine the number of classes (Nylund, Asparouhov, & Muthén, 2006) along with the BIC. When applicable, for nested LTA models that differ in the specification of change (not the number of classes), the traditional likelihood ratio test is used. The frequency table chi-square statistics (either Pearson or likelihood ratio-based) is not recommended for the LTA model since the chi-square distribution is not well approximated when there are large numbers of sparse cells. Other model diagnostic information can be used to compare model fit, such as a count of the significant bivariate residuals for each model (e.g., "TECH10" in M*plus*).

Results

The results are presented using five primary modeling steps: (1) cross-sectional exploration of the measurement model, (2) cross-sectional exploration of transitions, (3) exploration of the longitudinal LTA model without covariates, (4) inclusion of covariates and a mover-stayer variable (optional), and (5) inclusion of distal outcomes. We describe each step's relation to the larger picture of the LTA model and present results relevant to understanding peer victimization. In the interest of space, not all model results presented will be discussed in detail.

Step 0: Descriptive Statistics

The distribution and sample statistics of observed variables are explored in this step. Any emerging patterns are noted and the nature of missing data is explored. Tables 1 and 2 include the sample statistics for the observed variables used in the analysis. Table 1 includes the means of the six binary victimization items, presented by grade. Across all grades and items, the item means were below 0.50 and had similar values, indicating that overall, no single form of victimization was experienced more than another. Further, means on binary items (i.e., percent of students endorsing an item) indicated that on average, few students experienced victimization. Table 2 includes the sample statistics for the covariates and distal outcomes used in the analysis.

Step 1: Exploration of Measurement Model for Each Time Point

The flexibility of the latent variable framework allows for a range of exploratory measurement models to be used at each time point. Such models include factor analysis, latent class analysis, latent class factor analysis (LCFA), and factor mixture analysis (FMA) models. With the exception of the factor analysis model, all of these models provide a categorical latent variable part that can be used in the LTA model and are considered advanced applications of the LTA (see Muthen, in press). The exploration of the measurement model in each grade is useful since it determines whether similar classes emerge at each time point of interest. In some cases, developmental theory might predict changes in the structure and number of the classes (e.g., victimization classes based on frequency in sixth grade, but based on type in eighth grade).

More details of the measurement model used in this study can be found in Nylund et al. (2006). Key findings were that a three-class LCA solution emerged consistently across grades 6, 7 and 8, with the nonvictimized class always being largest (see Table 3). The three classes were differentiated by their probability of endorsing the victimization items (see Figure 1).

Step 2: Explore Transitions Based on the Cross-Sectional Results

Students can be classified into a latent victimization class at each time point based on the LCA-estimated posterior probabilities (i.e., a student's most likely class membership). These classifications can be used to create tables that forecast class change between adjacent grades (see Table 4). Though based on cross-sectional analyses, these values portray movement between the three victimization classes. The value of 0.46 for VI indicates that 46% of the students in the victimization class in grade 6 remained in the victimization class in grade 7. The values along the diagonal describe stability in victimization status and the off diagonals reflect movement. One interesting pattern that emerged is that when students transitioned (i.e., changed class in the subsequent grade) they were likely to transition into a class that reported less victimization.

Step 3: Explore Model Specifications of the Latent Transition Model without Covariates

In this step, substantive theory is integrated directly into the model through model specifications. In this application, we explored three important LTA model specifications: measurement invariance, stationary transition probabilities, and a second-order effect. For each, we fit models with different specifications and compared them using likelihood ratio tests. To avoid over-testing and relying too heavily on the dataset, model specifications were guided by developmental theory about victimization. We describe each of the specifications briefly.

Measurement invariance refers to how the observed variables relate to the underlying latent variable. There is a range of measurement invariance specifications, from full invariance (i.e., all measurement parameters are equal across time) to partial invariance (i.e., some item parameters are allowed to differ across time) to full measurement non-invariance (i.e., all parameters are different across time). Depending on the nature of the observed outcomes, the length of time considered, and the nature of the construct, measurement invariance may not be realistic. Thus, both theoretical and practical reasons determine whether measurement invariance should be assumed. In most applications of LTA, full measurement invariance is assumed for practical reasons since it ensures that the number and structure of the classes are the same across time and allows for a straightforward interpretation of the transition probabilities.

In this study, we explored full invariance, full noninvariance, and some partial invariance models. There was an improvement in fit by allowing the full noninvariance over full invariance, as expected. Of the partial invariance strategies, however, there was not a clear superior specification. Given the remarkably stable structure across grades (see Figure 1) and the validity of these classes (Nylund et al, 2006), we assumed full measurement invariance in this study. Assuming measurement invariance implied that the three victimization classes were the same across sixth, seventh and eight grades and no restrictions were made on the class sizes over time.

Stationary transition probabilities reflect the rate at which students are transitioning among the victimization classes is the same across all the transition points. Depending on the developmental process being studied, however, assuming similar transitions may not be realistic. These probabilities are also only relevant when covariates are not directly included (e.g., multiple group approach). Once covariates or second-order transitions are added, transition probabilities are not only a function of the previous time point, but also a student’s values on the covariates or transitions, making the assumption of invariant transition probabilities meaningless.

We fit two models, one with stationary transition probabilities and another without (i.e., a transition matrix was estimated for grade 6 to grade 7 and another for grade 7 to grade 8). Results indicated there is not a significant difference in the transition probabilities across time ($\chi^2 = 5.45$, $df = 6$, $p = 0.49$). That is, students were equally likely to move among the victimization classes across the two transition points. However, in this study, since we were particularly interested in covariate relationships, we did not impose stationary probabilities despite this result.

A *second-order effect* (i.e., lag-2 effect) implies that an individual’s state at one time point is dependent on not only the previous time point, but also two time points previous. This is relevant, for instance, to explore if there is a lasting effect of a state. For example, it could be that a student’s victimization experience in sixth grade has lasting effects that can be seen in their victimization status in eighth grade, two grades later.

We explored a second-order effect with the peer victimization data and compared model fit to a model with a first-order effect. Results indicated that the second-order transition model provides a significantly better fit ($\chi^2 = 38.2$, $df = 4$, $p < 0.01$), suggesting that there is a lasting effect of an individual's victimization experience in sixth grade that carries through to 8th grade, and further supports the decision of non-stationary transition probabilities.

Steps 4 and 5: Include Relevant Covariates, a Mover-Stayer Latent Class Variable (optional), and Distal Outcomes

The last two modeling steps include other variables that help describe the heterogeneity in change. First, we explored covariates and a mover-stayer variable. Since there are numerous ways of adding covariates, it is essential that substantive theory guide the approach that is used. In our model, we chose to examine whether gender, a time invariant covariate, can have a time specific effect on the victimization classes (i.e., a time varying effect). This allowed us to see if there were different percentages of girls and boys in certain victimization classes across time. Ethnicity was included as a control variable. We also examined whether the time varying covariates that were measured concurrently with the outcomes had time specific effects. For example, did depressive symptoms have differential effects across time or different relationships with the victim classes as students progressed through middle school?

The mover-stayer model (e.g., Langeheine & Van de Pol, 1994) is another way to model heterogeneity in development. A mover-stayer LTA uses a second-order latent class variable that classifies individuals as "movers" (students who change classes at any point during the study) or "stayers" (students who remain in the same class across the span of the study). The mover-stayer variable is important since it allows for the identification of students who remain in a given state across development (i.e., students who are chronically victimized). By estimating transition probabilities for movers only, the transition probabilities more accurately describe movement among the victimization classes since they do not include those who remain in the same victimization class across time (i.e., stayers).

Distal outcomes are thought to reflect consequences of the processes described by the LTA model. In our model we were interested in whether distal outcomes were predicted from the mover-stayer variable describing students' victimization. Specifically, we sought to determine whether students who remained constantly victimized across middle school reported more social worries in high school than students who remained constantly free from experiencing victimization. Relating a student's mover-stayer status to high school outcomes allowed us to empirically assess the consequences of being chronically victimized throughout middle school.

We present the results of the final two steps together since they involve the inclusion of variables that are either hypothesized correlates or consequences of growth and help to describe development. Figure 2 depicts our final model which involves the inclusion of time varying covariates (i.e., school safety, depressive symptoms, and social anxiety) and time invariant covariates (i.e., gender and ethnicity), that with the exception of ethnicity, were tested for time specific effects (i.e., an effect is estimated for each grade). In this diagram, the dependent variable (i.e., peer victimization) in the circle is the outcome of interest that is measured by a set of observed variables (i.e., individual binary items on the peer victimization measure, represented by boxes) at each time point. This model also includes a mover-stayer latent variable to capture stability in victimization status and demographic variables (i.e., gender and ethnicity) that are related to it. Finally, two high school (ninth grade) outcomes, physical symptoms and social worries, are included individually as distal outcomes.

Victimization classes. Table 5 displays the size of the three victimization classes for grades 6, 7, and 8 based on the final LTA model. Similar to the cross-sectional data (see Table 3) LTA revealed that the VI class starts at 28% in sixth grade and shrinks to 13% by the end of eighth grade while the nonvictimized class grows, starting at 28% and increasing to 51%. These class sizes are based on the longitudinal model, simultaneously taking into account the information provided by covariates, distal outcomes, and the mover-stayer variable.

Movers and stayers. In the final model, 75% of the sample are movers (i.e., students who move in and out of the victimization classes) and 25% are stayers (i.e., students who have the same victimization status all throughout middle school). Of the stayers, only 3% of the entire sample are classified as chronically victimized, 8% are chronically sometimes victimized, and the largest group, 13% of the sample, are chronically nonvictimized.

Among the 27 different patterns of movers, many reflected movement towards a less victimized class. Table 6 displays the mover-stayer patterns that reflected at least 1% of the sample. Some interesting patterns among the movers emerged. The most frequent patterns of movers were those students who started out in higher victimization classes and then transitioned into one with less victimization (e.g., SV, NV, NV, or SV, SV, NV). Note that some movers have patterns of a stayer (i.e., no change in victimization status during middle school): 11% were consistently sometimes victimized (SV, SV, SV) and 10% were consistently nonvictimized (NV, NV, NV). These students are deemed movers because they have covariate and distal outcome values that are very similar to movers, despite their stayer pattern. Movers that changed from a less to more victimized class (e.g., SV, VI, VI) were rare (only 10% of the sample cumulatively).

Covariates. The time-specific associations of the four covariates (i.e., gender, school safety, depressive systems, and anxiety) with victimization classes are presented in Table 7. Using the nonvictimized class (i.e., class 3) as the comparison group, for each grade and covariate, two comparisons were made: (1) the likelihood of being in the victimized compared to the nonvictimized class and (2) the likelihood of being in the sometimes victimized compared to the nonvictimized class. We highlight the key covariate findings from Table 7.

For all covariates, besides depressive symptoms, there were differential effects across time. In grade 6, boys and girls were equally likely to be in all three victimization classes. In grades 7 and 8, however, the gender logistic regression coefficient (or logit) for the victimized class (-0.65, $p < .001$) indicated that compared to the nonvictimized class, boys were more likely than girls to be in the victimized class. There were no gender differences among the sometimes and nonvictimized classes for any grade.

Results also indicated that in sixth grade, compared to the nonvictimized class, students in both the victimized and sometime victimized class felt significantly less safe in school. This result did not persist because by eighth grade there were no differences among the victimization classes for school safety. Similarly, there was a significant difference in students' social anxiety based on their victimization in grade 6. Compared to the nonvictimized class in 6th grade, students in the victimized class reported more social anxiety. These differences were not found in 7th and 8th grade. In all grades, students in the victimized and sometimes victimized classes had significantly more depressive symptoms than students in the nonvictimized class.

Results for the demographic variables (i.e., gender and ethnicity) that were related to the mover-stayer variable are presented at the bottom of Table 7. There was not a significant gender difference, indicating that boys and girls are equally likely to be movers and stayers. Compared to Caucasian students, Latino students are more likely to be in the stayer class.

Distal outcomes. Two distal outcome variables measured in the fall of 9th grade were allowed to differ as a function of mover-stayer status. Specifically, we focused on the impact of students who were chronically victimized compared to those who were chronically nonvictimized. Table

8 displays the means on the distal outcomes of those classified as stayers. We found that those who were classified as chronically victimized reported more physical symptoms and worries about their social success during high school than those who remain chronically nonvictimized.

Discussion

The goal of this paper was to demonstrate an advanced application of LTA, while providing useful steps for model testing and making a unique contribution to the peer victimization literature. Using LTA was particularly useful because the model empirically derived meaningful victimization classes (Step 1), described change among these classes during middle school (Steps 2 and 3), tested whether covariates differentiated students in the three classes (Step 4), identified movers and stayers (Step 4), and described high school outcomes of middle school victimization experiences (Step 5). We also demonstrated extensions not commonly used with LTA (e.g., second-order effects, mover-stayers). Presenting the analyses in five steps highlighted intermediate modeling results that were ultimately validated in the final model. For example, in Step 2 cross-sectional results were used to create proxy transition tables and hypothesize that when students transition, they tend to move into less victimized classes. This hypothesis was supported in the final model.

There were many strengths of using LTA to explore developmental questions based on change among distinct groups (e.g., victimized, nonvictimized). LTA uses a measurement model to create the groups, predictor variables to serve to validate the groups, and a structural model to describe change over time in group membership. An alternative approach would be to a priori assign individuals to victimization groups and then use a longitudinal model to describe transitions. LTA has the ability to do both simultaneously. Further, with LTA, the formations of groups, as well as the parameters describing transitions among groups over time, are all informed by variables included in the analysis (i.e., covariates, mover-stayer, and distal outcomes).

Developmental understanding of peer victimization. Three key substantive findings add to the understanding of peer victimization during development. First, previous cross-sectional findings about peer victimization prevalence (e.g., Nansel et al., 2001) were supported with longitudinal data. The normative pattern was for students to move to less victimized classes over time. Patterns of increasing victimization were exceedingly rare. Second, prior states were associated with maladjustment in two different ways. A lag-2 effect indicated that students' prior victimization predicted their current victimization and this effect lingered at least 2 years (6^{th} grade predicted 8^{th} grade victimization). Also, the manner in which students moved into and out of victimization classes, or stayed in the same class, predicted maladjustment even into high school (i.e., more physical symptoms and social worries resulted from being a chronic victim).

Third, we demonstrated time specific effects of a variety of covariates that are typically associated with peer victimization. For example, there were minimal gender effects: gender did not predict being a mover or stayer, nor did it predict victimization class in sixth grade. By grades 7 and 8, however, boys were more likely to be in the victimization class. The opposite was found for perceived school safety and anxiety. These variables differentiated the victim classes in sixth, but not seventh and eighth grades. In comparison, depressive symptoms consistently differentiated victim classes throughout the course of middle school. Combined, these findings suggest that as kids become the oldest and biggest within their schools they are less concerned about safety, but feelings of personal distress associated with being a victim (i.e., depressive symptoms) are maintained throughout. It will be important for further research to systematically examine both the more temporary/grade-related consequences of victimization and the long-term negative consequences of victimization. LTA allows both such examinations.

Limitations and future directions. The limitations of this study involve methodological and substantive ones. For example, LTA is a longitudinal model that is particularly useful in modeling changes in discrete groups that is focused on modeling time point to time point change. However, there are instances when the developmental research questions would not be addressed by this model (e.g., questions aimed at addressing the average rate of change). Additionally, although we tried to make the modeling steps as general as possible, model specifications vary from study to study, especially when very specific research questions are being explored. Also, we assumed full measurement invariance. Given the stability of the classes in this study this is a reasonable assumption. In general, with a large number of invariance strategies possible for models with many time points and classes, it becomes a very difficult task to determine which partial measurement invariance strategy is best, even with strong substantive theory. More research is needed on the best way to explore measurement invariance issues in LTA models.

In addition, we only used six items to capture peer victimization. It could be that there are other, yet to be identified forms of victimization that should have been included. Also, we linked victimization to only two outcomes in high school that are measured in their first semester in high school. Further research is needed to explore additional distal outcomes and to integrate high school covariates (e.g., high school climate, social support) that might illuminate the conditions under which the negative consequences of middle school peer victimization follow students into their high school tenure.

The flexibility of new longitudinal models has begun to address the complexity inherent in human development. Careful and systematic application of these models can provide unique insight about the nature of peer victimization and foster new directions for further research.

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Appendix A: Descriptions of variable names used in analyses

To help the reader better understand the syntax provided, and because Mplus only allows variable names up to 8 characters long, we have provided a definition for each of the variables used in the syntax.

id = student id

school = indicates which of 11 schools students attend

sex = 0 = male, 1 = female

ethnic = 1 = Caucasian, 2 = African American, 3 = Latino, 4 = Asian, 5 = multiethnic

schsafe6, schsafe7, schsafe8 = school safety composite for grades 6, 7, and 8, respectively

socanx6, socanx7, socanx8 = social anxiety composite for grades 6, 7, and 8, respectively

depress6, depress7, depress8 = depressive symptoms composite for grades 6, 7, and 8

vict1s6 to vict6s6 = 6 individual binary victimization variables for spring of grade 6

vict1s7 to vict6s7 = 6 individual binary victimization variables for spring of grade 7

vict1s8 to vict6s8 = 6 individual binary victimization variables for spring of grade 8

physsx9 = physical symptoms composite for grade 9

hsworry9 = social worries in high school for grade 9

Later, the gender and ethnicity variables are recoded/renamed such that:

female = 0 = male, 1 = female

afam = 0 = Caucaisan, 1 = African American
latino = 0 = Caucasian, 1 = Latino
asian = 0 = Caucasian, 1 = Asian
multi = 0 = Caucasian, 1 = multiethnic

Appendix B: Mplus Syntax for the LCA measurement model with three classes.

```
TITLE:  Sixth grade 3-class exploratory LCA model
DATA: File is longitdataset.dat;

VARIABLE:
Names are id school sex ethnic
    schsafe6 socanx6 depress6
    schsafe7 socanx7 depress7
    schsafe8 socanx8 depress8
    vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
    vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
    vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8
    physsx9 hsworry9;

IDVARIABLE  =  id;
MISSING are all(9999);

CLASSES =  c(3);
USEVAR =  vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6;
CATEGORICAL  = vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6;
CLUSTER = school;

ANALYSIS:  TYPE  =   mixture missing complex;
    STARTS  =  50 5;
    LRTSTARTS  =  10 2 10 2;
    PROCESS =  2;

OUTPUT:  TECH1 TECH8 TECH14;

PLOT: type is plot3 ;
  SERIES  =  vict1s6(1) vict2s6 (2) vict3s6 (3) vict4s6(4) vict5s6(5) vict6s6(6);

SAVEDATA:
         SAVE  =  cprobabilities ;
         FILE is  grade6_3c_cprob.dat;
```

Appendix C: Mplus Syntax for Invariant Transition Probabilities

```
TITLE:  LTA model with invariant transition probabilities
        LCA full measurement invariance.

VARIABLE:
  Names are id school sex ethnic
  schsafe6 socanx6 depress6
  schsafe7 socanx7 depress7
  schsafe8 socanx8 depress8
  vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
  vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
  vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8     physsx9 hsworry9;

IDVARIABLE  =  id;
MISSING are all(9999);
CATEGORICAL  =  vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
           vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
           vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8 ;
CLASSES =  c1(3)  c2(3)  c3(3);
CLUSTER = school;

USEVAR =   vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
        vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
        vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8 ;

ANALYSIS: Type =  mixture missing complex;
   STARTS  =  50 10;
   PROCESS =  2;

MODEL:
%Overall%     ! Constraining transition probabilities to be the same
   [c2#1] (101);
   [c2#2] (102);
   [c3#1] (101);
   [c3#2] (102);

  c2#1 on c1#1 (111);
  c2#1 on c1#2 (112);
  c2#2 on c1#1 (113);
  c2#2 on c1#2 (114);

  c3#1 on c2#1 (111);
  c3#1 on c2#2 (112);
  c3#2 on c2#1 (113);
  c3#2 on c2#2 (114);
```

```
MODEL c1:          ! Measurement model for grade 6
 %c1#1%
   [vict1s6$1- vict6s6$1]  (1-6); !  The (1-6) labeling the item thresholds, which will be held
                                   !equal across time
%c1#2%
    [vict1s6$1- vict6s6$1]  (7-12);
%c1#3%
    [vict1s6$1- vict6s6$1]  (13-18);

MODEL c2:          ! Measurement model for grade 7
%c2#1%
    [vict1s7$1- vict6s7$1]  (1-6);
%c2#2%
    [vict1s7$1- vict6s7$1]  (7-12);
%c2#3%
    [vict1s7$1- vict6s7$1]  (13-18);

MODEL c3:          ! Measurement model for grade 8
%c3#1%
    [vict1s8$1- vict6s8$1]  (1-6);
%c3#2%
    [vict1s8$1- vict6s8$1]  (7-12);
%c3#3%
    [vict1s8$1- vict6s8$1]  (13-18);
```

Appendix D: Mplus Syntax for second-order LTA model

```
TITLE:  LTA Model with second-order effect, no covariates,
          LCA full measurement invariance.
DATA: File is longitdataset.dat;

VARIABLE:
  Names are id school sex ethnic schsafe6 socanx6 depress6
    schsafe7 socanx7 depress7 schsafe8 socanx8 depress8
    vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
    vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
    vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8
    physym9 hsworry9;

IDVARIABLE  =  id;
MISSING are all(9999);
CATEGORICAL  =  vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
              vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
              vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8 ;
CLASSES =  c1(3)  c2(3)  c3(3);
CLUSTER = school;

USEVAR =   vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
           vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
           vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8 ;

ANALYSIS: TYPE =  mixture missing complex;
     STARTS=  50 10;
     PROCESS  =  2;

MODEL:
%Overall%
  c2#1 on c1#1;          ! Time 2 on Time 1 (first-order effect)
  c2#1 on c1#2;
  c2#2 on c1#1;
  c2#2 on c1#2;

  c3#1 on c2#1;          ! Time 3 on Time 2 (first-order effect)
  c3#1 on c2#2;
  c3#2 on c2#1;
  c3#2 on c2#2;

  c3#1 on c1#1;          ! Time 3 on Time 1 (second-order effect)
  c3#1 on c1#2;
  c3#2 on c1#1;
  c3#2 on c1#2;
```

```
MODEL c1:
%c1#1%
   [vict1s6$1- vict6s6$1]  (1-6);
%c1#2%
   [vict1s6$1- vict6s6$1]  (7-12);
%c1#3%
   [vict1s6$1- vict6s6$1]  (13-18);

MODEL c2:
%c2#1%
   [vict1s7$1- vict6s7$1]  (1-6);
%c2#2%
   [vict1s7$1- vict6s7$1]  (7-12);
%c2#3%
   [vict1s7$1- vict6s7$1]  (13-18);

MODEL c3:
%c3#1%
   [vict1s8$1- vict6s8$1]  (1-6);
%c3#2%
   [vict1s8$1- vict6s8$1]  (7-12);
%c3#3%
   [vict1s8$1- vict6s8$1]  (13-18);

PLOT: Type  =  plot3 ;
series  =  vict1s6 (1) vict2s6 (2) vict3s6 (3) vict4s6(4) vict5s6(5) vict6s6(6)
       vict1s7 (7) vict2s7 (8) vict3s7 (9) vict4s7(10) vict5s7(11) vict6s7(12)
       vict1s8 (13) vict2s8 (14) vict3s8(15) vict4s8(16) vict5s8(17) vict6s8(18);

OUTPUT: TECH1 TECH10;
```

Appendix D: Mplus Syntax for first-order LTA model with covariates, mover-stayer latent variable, distal outcome (physical symptoms).

```
TITLE: Final LTA model with M-S variable, covariate, and distal outcome.

DATA: File is longitdataset.dat;
VARIABLE:
  Names are id school sex ethnic schsafe6 socanx6 depress6
     schsafe7 socanx7 depress7
     schsafe8 socanx8 depress8
     vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
     vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
     vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8
     physym9  hsworry9;

IDVARIABLE  =  id;
MISSING are all(9999);
CATEGORICAL  =  vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
                vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
                vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8;
CLASSES =  c1(3)  c2(3)  c3(3);
CLUSTER = school;

USEVAR =   schsafe6 depress6 socanx6
    schsafe7 depress7 socanx7
    schsafe8 depress8 socanx8
    physsx9
    vict1s6 vict2s6 vict3s6 vict4s6 vict5s6 vict6s6
    vict1s7 vict2s7 vict3s7 vict4s7 vict5s7 vict6s7
    vict1s8 vict2s8 vict3s8 vict4s8 vict5s8 vict6s8
    female afam latino asian multi;
  CLUSTER = school;
  CLASSES = c (2) c1(3) c2(3) c3(3);

    DEFINE:
        IF (sex eq 0) THEN female=0;
        IF (sex eq 1) THEN female=1;

        IF (ethnic eq 2) THEN afam=1;
        IF (ethnic ne 2) THEN afam=0;
        IF (ethnic eq 3) THEN latino=1;
        IF (ethnic ne 3) THEN latino=0;
        IF (ethnic eq 4) THEN asian=1;
        IF (ethnic ne 4) THEN asian=0;
        IF (ethnic eq 5) THEN multi=1;
        IF (ethnic eq 6) THEN multi=1;
```

```
ANALYSIS: Type= mixture missing complex;
    STARTS=225 50;
    PROCESS=2;

MODEL:
        %overall%
        !c is the mover-stayer latent variable
        !c#1 is the mover class
        !c#2 is the stayer class

        !c1, c2, c3 are the time-specific victimization classes

  ! Relating c1 and c2 to c:  (Movers)
        [c1#1];
        [c1#2];
        [c2#1];
        [c2#2];
        c1#1 on c#1;
        c1#2 on c#1;
        c2#1 on c#1;
        c2#2 on c#1;

  ! Relating c2 and c3 to c:  (Stayers)
        [c2#1@-15];     !"a1" - probability of transitioning from VI
                        ! at grade 6 to SV at grade 7 is fixed
                        ! at zero for the stayer class
         [c2#2@-15];    ! These statements are fixing cells of transition matrix for stayers
         [c3#1@-15];
         [c3#2@-15];

         c1#1 c1#2 on female schsafe6 depress6 socanx6;
         c2#1 c2#2 on female schsafe7 depress7 socanx7;
         c3#1 c3#2 on female schsafe8 depress8 socanx8;
   ! the above statements regresses the time specific victim classes on the four covariates

          c#1 on female afam latino asian multi;
   ! the above statement regresses the mover/stayer variable on gender and ethnicity

MODEL c:
  %c#1%                 !mover class
    c2#1 on c1#1;       !"b11" – mover class transition prob's are freely estimated
    c2#1 on c1#2;       !b12
    c2#2 on c1#1;       !b21
    c2#2 on c1#2;       !b22
```

```
    c3#1 on c2#1;               !"b11" - !mover class transition prob's are freely estimated
    c3#1 on c2#2;               !b12
    c3#2 on c2#1;               !b21
    c3#2 on c2#2;               !b22
     [physsx9] ;                         ! estimating a mean on the distal for all movers

 %c#2%                          !stayer class
    c2#1 on c1#1@30;            !"b11" - stayer class has prob 1 of staying
    c2#1 on c1#2@-45;           !b12
    c2#2 on c1#1@-45;           !b21
    c2#2 on c1#2@30;            !b22

    c3#1 on c2#1@30;            !"b11" - stayer class has prob 1 of staying
    c3#1 on c2#2@-45;           !b12
    c3#2 on c2#1@-45;           !b21
    c3#2 on c2#2@30;            !b22
     [physsx9] ;

MODEL c.c1:
   %c#1.c1#1%                            !c#1.c1#1 are the movers who are VI in Grade 6
     [vict1s6$1- vict6s6$1]  (1-6);

  %c#1.c1#2%                             !c#1.c1#2 are the movers who are SV in Grade 6
      [vict1s6$1- vict6s6$1]  (7-12);

  %c#1.c1#3%                             !c#1.c1#3 are the movers who are NV in Grade 6
     [vict1s6$1- vict6s6$1]  (13-18);

  %c#2.c1#1%                             !c#2.c1#1 are the stayers who are VI in Grade 6
     [vict1s6$1- vict6s6$1]  (1-6);
         [physsx9] (p3);        ! Estimating a mean for the VI stayers
 %c#2.c1#2%
      [vict1s6$1- vict6s6$1]  (7-12);   !c#2.c1#2 are the stayers who are SV in Grade 6
       [physsx9] (p6);                   ! Estimating a mean for the SV stayers
 %c#2.c1#3%
     [vict1s6$1- vict6s6$1]  (13-18);!c#2.c1#3 are the stayers who are in NV in Grade 6
     [physsx9] (p9);                     ! Estimating a mean for the NV stayers

MODEL c.c2:
   %c#1.c2#1%                            !c#1.c2#1 are the movers who are in VI in Grade 7
      [vict1s7$1- vict6s7$1]  (1-6);

   %c#1.c2#2%
      [vict1s7$1- vict6s7$1]  (7-12); !c#1.c2#2 are the movers who are in SV in Grade 7
```

```
  %c#1.c2#3%
    [vict1s7$1- vict6s7$1]  (13-18); !c#1.c2#3 are movers who are in NV in Grade 7

  %c#2.c2#1%
    [vict1s7$1- vict6s7$1]  (1-6);

  %c#2.c2#2%
    [vict1s7$1- vict6s7$1]  (7-12);

  %c#2.c2#3%
    [vict1s7$1- vict6s7$1]  (13-18);

MODEL c.c3:
   %c#1.c3#1%
     [vict1s8$1- vict6s8$1]  (1-6);

   %c#1.c3#2%
      [vict1s8$1- vict6s8$1]  (7-12);

   %c#1.c3#3%
      [vict1s8$1- vict6s8$1]  (13-18);

   %c#2.c3#1%
     [vict1s8$1- vict6s8$1]  (1-6);

    %c#2.c3#2%
      [vict1s8$1- vict6s8$1]  (7-12);

    %c#2.c3#3%
      [vict1s8$1- vict6s8$1]  (13-18);

MODEL TEST:
        p3=p6;
        p3=p9;
        p6=p9;
SAVEDATA: File is ltafinal.dat;
   SAVE=cprobabilities;
```

Footnote

1. The design of the longitudinal middle school study was such that we did not continue to follow students if they transferred out of one of our 11 target middle schools. We calculated an expected retention rate for our sample based on the average school mobility rate (i.e., percentage of students who first attended the school that year) for each of the schools as reported by the California Department of Education for each of the three years of the study. We calculated this expected retention rate in the following way: First, we multiplied the initial sample in each of the schools by that school's overall mobility rate in Year 1. This yielded an expected n for Year 2. Second, we multiplied the expected n for Year 2 by that school's overall mobility rate for Year 2. This yielded an expected n for Year 3. Third, we summed all of the expected sample sizes for Year 3 across the 11 schools, which yielded an expected total sample as of Year 3. Finally, we divided the expected total Year 3 sample by our original n. This yielded an expected retention rate of 59% across the 3 years of the study. Our participation rate of 75% at the end of year 3 is better than expected given the average student turnover for the schools in our study.
2. This is specified using “Type = cluster” in Mplus. Generally, at least 20 cluster units are recommended for this adjustment.

3. Table 1. Observed Sample Size, Mean, and Standard Deviation for the Six Binary Peer Victimization Survey Items for Grade 6, Grade 7, and Grade 8.

Variable	Grade 6			Grade 7			Grade 8		
	N	M (SD)		N	M (SD)		N	M (SD)	
Called Bad Names	1931	0.37	(0.48)	1707	0.25	(0.43)	1565	0.20	(0.40)
Talked About	1943	0.33	(0.47)	1737	0.26	(0.44)	1588	0.23	(0.42)
Picked On	1936	0.28	(0.45)	1722	0.19	(0.39)	1582	0.14	(0.35)
Hit and Pushed	1936	0.21	(0.41)	1735	0.15	(0.36)	1588	0.12	(0.32)
Things Taken/									
Messed Up	1943	0.29	(0.45)	1732	0.19	(0.39)	1590	0.15	(0.35)
Laughed At	1942	0.30	(0.46)	1733	0.20	(0.40)	1594	0.18	(0.38)

Table 2. Mean and standard deviation for covariates for school safety, depressive symptoms, and social worries for grades 6, 7, and 8 and high school distal outcomes.

Measure	Grade 6 *M* (*SD*)	Grade 7 *M* (*SD*)	Grade 8 *M* (*SD*)	Grade 9 *M (SD)*
School Safety	0.25 (0.31)	0.24 (0.31)	0.24 (0.30)	**
Depression	2.18 (0.76)	1.99 (0.73)	1.84 (0.68)	**
Social Anxiety	4.27 (0.60)	4.38 (0.61)	3.91(0.38)	**
Social Worries	*	*	*	1.70 (0.51)
Physical Symptoms	*	*	*	1.69 (0.49)

*Indicates variables that are not included as middle school covariates.

**Indicates variable that are not included as high school distal outcomes.

Table 3. Percent of students in of the victimization class in grades 6 through 8 based on cross-sectional LCA results.

Classes	Grade 6	Grade 7	Grade 8
Victimized	15%	18%	6%
Sometimes Victimized	31%	33%	25%
Nonvictimized	50%	49%	69%

Note: VI class = victimized class, SV class = sometimes victimized class, NV class = nonvictimized class.

Table 4. Preliminary transition tables based on victimization classifications from the cross-sectional LCA modeling results.

	Grade 7				Grade 8		
Grade 6	VI	SV	NV	Grade 7	VI	SV	NV
VI	0.46	0.31	0.24	VI	0.19	0.43	0.38
SV	0.18	0.34	0.48	SV	0.05	0.22	0.74
NV	0.06	0.24	0.70	NV	0.02	0.11	0.87

Note: VI class = victimized class, SV class = sometimes victimized class, NV class = nonvictimized class.

Table 5. Size of victimization classes based on the final LTA model with covariates, movers-stayer variable and a distal outcome.

Class	Grade 6	Grade 7	Grade 8
VI	28%	17%	13%
SV	44%	41%	36%
NV	28%	43%	51%

Note: VI class = victimized class, SV class = sometimes victimized class, NV class = nonvictimized class.

Table 6. Percent of students in each pattern of victimization of experiences, ordered by the frequency of the patterns, by movers then stayers.

Class	Grade 6	Grade 7	Grade 8	Frequency
Movers	SV	NV	NV	14%
(75%)	SV	SV	SV	11%
	NV	NV	NV	10%
	VI	SV	SV	7%
	VI	VI	SV	5%
	SV	SV	NV	5%
	VI	VI	VI	4%
	VI	NV	NV	3%
	VI	SV	NV	3%
	SV	SV	VI	2%
	NV	SV	SV	2%
	VI	SV	VI	2%
	SV	VI	SV	2%
	SV	VI	VI	1%
	NV	SV	NV	1%
	VI	VI	NV	1%
	SV	NV	SV	1%

Table 6 (continued). Percent of students in each pattern of victimization of experiences, ordered by the frequency of the patterns, by movers then stayers.

Class	Grade 6	Grade 7	Grade 8	Frequency
Stayers	NV	NV	NV	13%
(25%)	SV	SV	SV	8%
	VI	VI	VI	3%

Note: VI class = victimized class, SV class = sometimes victimized class, NV class = nonvictimized class. Only patterns that represented over 1% of the sample were included.

Table 7. Log odds coefficients for three-class model with gender (boys = 0, girls = 1), school safety, depression and anxiety as covariates, the nonvictimized class is the comparison group for victimization class comparisons, and the mover class as the comparison group for the mover-stayer comparisons (bottom of the table).

Class	*Effect*	*Logit*	*S.E.*	*t*	*odds ratio*
Grade 6					
Victimized	Gender	-0.65	0.35	-1.88	0.52
	School Safety	-2.69*	0.68	-3.99	0.07
	Depression	6.20*	1.56	3.99	492.75
	Anxiety	0.47*	0.20	2.36	1.60
Sometimes Victimized	Gender	-0.09	0.41	-0.22	0.91
	School Safety	-1.50*	0.69	-2.19	0.22
	Depression	4.66*	1.50	3.10	105.64
	Anxiety	0.28	0.26	1.06	1.32
Grade 7					
Victimized	Gender	-0.66*	0.34	-1.96	0.52
	School Safety	-1.27*	0.35	-3.58	0.28
	Depression	4.49*	0.82	5.47	89.03
	Anxiety	0.23	0.33	0.69	1.26

Table 7 Continued.

Grade 7					
Sometimes Victimized	Gender	0.05	0.27	0.19	1.05
	School Safety	-0.24	0.35	-0.68	0.79
	Depression	3.46*	0.80	4.35	31.88
	Anxiety	0.17	0.21	0.83	1.19
Grade 8					
Victimized	Gender	-1.10*	0.52	-2.12	0.33
	School Safety	1.03	0.54	1.88	2.79
	Depression	5.78*	2.47	2.34	322.47
	Anxiety	1.39	1.10	1.26	4.03
Sometimes Victimized	Gender	-0.82	0.45	-1.84	0.44
	School Safety	1.13	0.70	1.61	3.10
	Depression	4.55*	2.20	2.07	94.35
	Anxiety	1.24	1.14	1.09	3.45
Mover-Stayer					
	Gender	-0.26	0.34	-0.78	0.77
	African American	1.26	0.77	1.63	3.52
	Latino	1.00*	0.50	2.01	2.70
	Asian	-0.32	0.42	-0.78	0.72
	Multiethnic	0.27	0.31	0.90	1.32

Table 8. Estimated means on the high school distal outcomes based on the final LTA model.

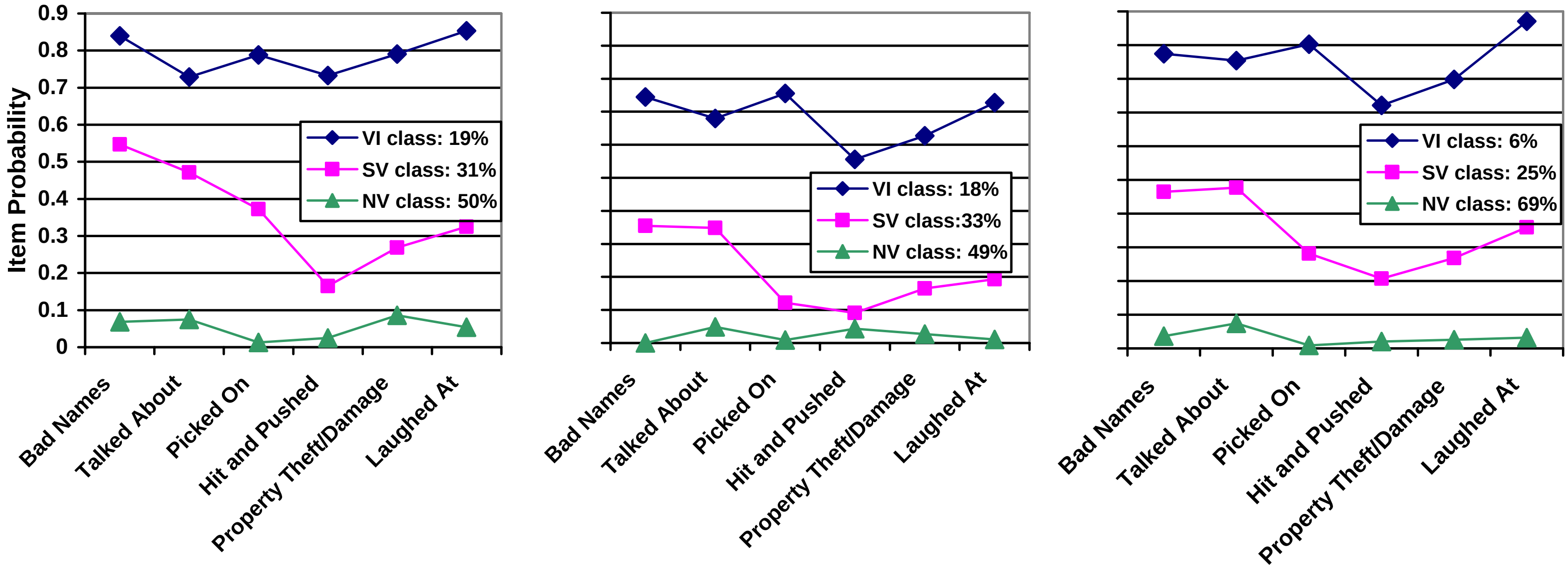
Measure	NV	SV	VI
	M (*SD*)	*M* (*SD*)	*M* (*SD*)
Social Worries	0.50 (0.06)	1.61 (0.20)	1.38 (0.12)
Physical Symptoms	1.82 (0.09)	1.84 (0.19)	1.55 (0.13)

Figure Captions

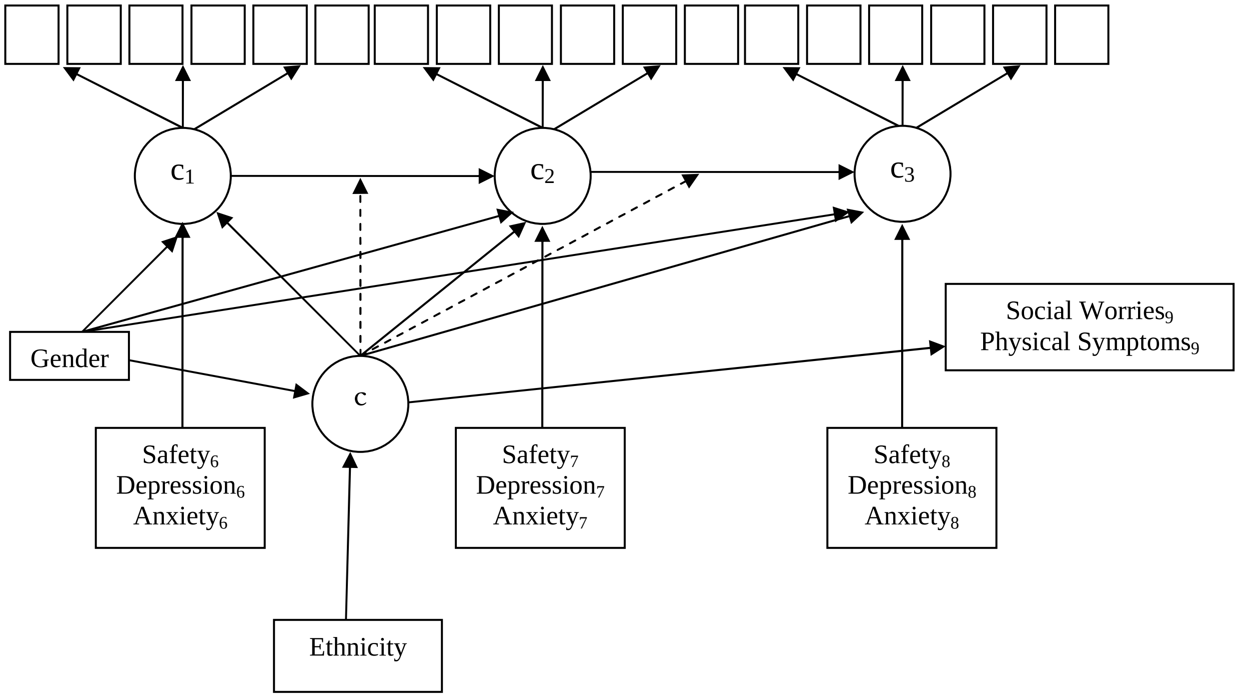
Figure 1. Conditional item probability plots for the 3-class models for grades 6, 7, and 8. Class size information is presented in the legend.

Figure 2. Final LTA model that includes time varying covariates, a mover-stayer latent variable, and distal outcomes.

Spring 6th Grade (N = 1931) Spring 7th Grade (N = 1723) Spring 8th Grade (N = 1558)



Note: VI class = victimized class, SV class = sometimes victimized class, NV class = nonvictimized class.


c1
c2
c3
Social Worries9
Physical Symptoms9
Gender
c
Safety6
Depression6
Anxiety6
Safety7
Depression7
Anxiety7
Safety8
Depression8
Anxiety8
Ethnicity