Child Development, November/December 2007, Volume 78, Number 6, Pages 1706 – 1722

Subtypes, Severity, and Structural Stability of Peer Victimization: What Does Latent Class Analysis Say?

Karen Nylund
University of California, Los Angeles

Amy Bellmore
University of Wisconsin—Madison

Adrienne Nishina
University of California, Davis

Sandra Graham
University of California, Los Angeles

This study uses latent class analysis (LCA) to empirically identify victimization groups during middle school. Approximately 2,000 urban, public middle school students (mean age in sixth grade = 11.57) reported on their peer victimization during the Fall and Spring semesters of their sixth, seventh, and eighth grades. Independent LCA analyses at each semester yielded 3 victim classes based on victimization degree rather than type (e.g., physical vs. relational). The most victimized class always represented the smallest proportion of the sample, decreasing from 20% in sixth grade to 6% by the end of eighth grade. This victimized class also always reported feeling less safe at school concurrently and more depressed than others 1 semester later, illustrating the validity of the LCA approach.

It is now well established in the literature that peer victimization is associated with a host of adjustment difficulties during childhood and adolescence, ranging from psychological maladjustment and peer rejection to physical health sequelae (e.g., physical complaints, frequent nurse visits, school absences) and academic problems (e.g., poorer school performance) (Juvonen & Graham, 2001). Nevertheless, critical gaps in our understanding of students' peer victimization experiences remain. For example, there are inconsistencies in the criteria researchers use for identifying victims and nonvictims (see Ladd & Kochenderfer-Ladd, 2002; Solberg & Olweus, 2003). Moreover, we know little about the developmental course of peer victimization in terms of specifying whether students are more at risk for victimization at specific points in development or whether the nature of peer victimization experiences changes over time. The two main goals of the present study are to: (a) provide an illustrative example of a person-centered latent variable approach, latent class analysis (LCA) and (b) identify and assess the structural stability of victimization subgroups at six different time points across 3 years of middle school.

How Are Victim Groups Defined?

Classifying students into extreme groups is a useful technique for understanding individual differences in development (Magnusson & Cairns, 1996) and is employed by peer relations researchers interested in subgroups of aggressors and victims (e.g., Schwartz, 2000). When classifying students into different victimization risk groups—for example, to predict maladjustment—it is important that the groups accurately reflect the key differences between students. However, some studies classify students into groups based on victimization severity or frequency, whereas others seek to understand differences in risk based on experiencing different forms of peer victimization. When such different criteria are used, it becomes difficult to establish consistent subgroup differences.

Victim groups based on severity. Studies that specify victimization groups based on severity typically rely on standard deviations from the sample mean to classify students into groups, such as victims and nonvictims (e.g., Graham, Bellmore, & Mize, 2006; Graham & Juvoven, 1998; Juvonen, Graham, & Schuster, 2003; Olweus, 1993a; Perry, Kusel, & Perry, 1988; Schwartz, 2000). This method often relies on self-ratings (e.g., frequency of victimization experiences) and peer nominations (e.g., strength of victim reputation among classmates). Although this classification yields valid associations between extreme group membership and social – psychological functioning, there are several potential problems with this approach. First, there are no clear guidelines as to where to place cutoff scores or how many groups to create,

Correspondence concerning this article should be addressed to Karen Nylund, Department of Education, University of California, Los Angeles, GSE&IS Box 951521, 2027 Moore Hall, Los Angeles, CA 90095-1521. Electronic mail may be sent to knylund@ucla.edu.

regardless of whether raw scores or z-scores are used. Second, when standardized cutoffs are utilized (i.e., z-scores), a student's classification then becomes dependent on both their own victimization score as well as variations in victimization among their peers. And, in some situations, that may not be the main question of interest. For example, consider two different samples of students who both report on their victimization experiences on a scale ranging from 1 to 5. Imagine that in Sample A, the mean victimization score is 3, with a standard deviation of 1.5. In Sample B, the mean for victimization is 3.5, with a standard deviation of .75. Using a 1 standard deviation cutoff rule, a student with a score of 4.3 would not be classified as a victim in Sample A but would be considered a victim in Sample B.

Victim groups based on form of victimization. Another hotly contested issue in the study of peer-directed aggression that has yet to be resolved is that of the form(s) that it takes (see Archer & Coyne, 2005; Little, Jones, Henrich, & Hawley, 2003). There appear to be different forms of peer victimization (cf. physical, verbal, relational) and some researchers propose that it is important to distinguish between victims who experience physical harassment and those who are targets of more covert intimidation tactics, such as social exclusion (see Smith, Cowie, Olafsson, & Liefooghe, 2002). Those who emphasize these distinctions suggest that there are gender differences in frequency and consequences depending on the form of victimization (Crick & Bigbee, 1998; Paquette & Underwood, 1999; Storch, Nock, Masia-Warner, & Barlas, 2003). For example, some researchers have found that girls are less likely to be targets and perpetrators of overt and direct (i.e., verbal and physical) forms of aggression (Crick & Bigbee, 1998; Nansel et al., 2001; Paquette & Underwood, 1999). Crick, Casas, and Nelson (2002) also argue that the consequences for girls who are victims of relational aggression may be more severe than for boys. Thus, distinctions among different types of victimization experiences are potentially relevant when analyzing gender differences.

Classification of victims by types of experience is questionable in light of empirical evidence showing that different forms of victimization are highly correlated and that many targets are victimized in various ways. For example, Bellmore and Cillessen (2006) reported alphas above .90 of middle school students' composite peer-reported victimization scores based on general (e.g., "picked on"), physical, and relational victimization nomination items. With a younger sample of children (i.e., kindergarten through fourth grade), Ladd and Kochenderfer-Ladd (2002) reported alphas ranging from .72 to .79 on 4-item self-report scales of victimization where each item reflected a different type of victimization (i.e., physical, direct verbal, indirect verbal, general). These high intercorrelations suggest that children who experience one type of victimization also experience the other types of victimization measured in these studies. Additionally, there is evidence to suggest that there are no differences in the daily psychological consequences of victimization based on victimization type (Nishina & Juvonen, 2005).

Developmental Considerations in Determining Victim Groups

Correctly classifying students into victim groups requires knowledge about the developmental course of peer victimization across childhood and adolescence. Variations in the prevalence and/or forms of victimization experienced at different ages or grades may exist as a function of the individual or contextual characteristics that are present at different points in development (Smith, Madsen, & Moody, 1999). The middle school years promise to be an especially important period during which to study the developmental course of peer victimization for several reasons. First, research suggests that during adolescence, victims of peer harassment are among the most rejected students in their peer group (Boivin, Hymel, & Hodges, 2001). Second, several recent large, nationally representative studies have found that at least from a cross-sectional perspective, the frequency and prevalence of peer victimization peaks during the early middle school years (e.g., Kaufman et al., 1999; Nansel et al., 2001). That is, the percentage of students who report being victimized at least occasionally by their peers is highest during sixth grade, when students are typically in their first year of middle school, and decreases somewhat steadily during the later middle school years. These cross-sectional data suggest that for some students, peer victimization experiences may be largely confined to the early middle school years, though this remains an empirical question to be answered with longitudinal data.

We also know very little about variations in the forms of peer-directed aggression across development (Underwood, Galen, & Paquette, 2001). For example, it could be that younger students do not distinguish between some types of victimization but they begin to make such distinctions as they get older (e.g., covert relational vs. overt physical aggression) (Smith et al., 2002). Alternatively, it could be that certain types of victimization are relatively infrequent compared to others and that their relative frequency changes with age (Mynard & Joseph, 2000). For instance, the frequency of relational, compared to physical, victimization might be lower during preadolescence but increase steadily across the adolescent years. Boys and girls might also start experiencing distinct forms of peer maltreatment as they get older (Archer & Coyne, 2005). Some individuals might get victimized in multiple ways, whereas others might only experience one type of maltreatment (e.g., physical victimization or covert social manipulation). Note that neither the overall prevalence across grade levels and gender nor developmental differences in the nature of peer victimization experiences are issues that could be adequately addressed by classifying students into victimization groups based on cutoff criteria.

LCA: An Alternative Approach

The present study used a person-centered latent variable approach to address the debate concerning victimization type and to explore the developmental course of peer victimization during adolescence. As noted above, researchers interested in examining differences between victim types have commonly classified children into groups based on cutoff scores. Despite its utility, this method imposes differences between children that may not be meaningful or may result in classification errors including false positives and false negatives, and may dampen the ability to predict differences in psychosocial adjustment. In addition to these measurement problems, inaccurate cut points also have important practical implications for estimating the prevalence of victimization and for successfully designing and implementing interventions (Solberg & Olweus, 2003).

LCA, conceptually similar to cluster analysis, identifies latent classes based on observed response patterns (Clogg, 1988; Lazarsfeld & Henry, 1968; McCutcheon, 1987). Rather than relying on predetermined cut points, this multivariate approach assumes an underlying categorical latent variable that determines an individual's class membership. The observed classes may differ on different dimensions of victimization (i.e., the form of victimization), on relative frequency, or both frequency and dimensions. For example, some students may experience an abundance of all types of victimization, whereas other students may experience only one type. LCA allows for all such possibilities and illuminates different profiles based on students' responses to all items.

As an analytic approach, LCA offers several benefits. Unlike cluster analysis, LCA is model based or probabilistic, which implies that the model can be replicated with an independent sample (Muthén & Muthén, 2000). Further, LCA does not necessitate standardizing variables and allows the inclusion of predictor and outcome variables simultaneously in the model (i.e. covariates and distal outcomes). Also, unlike traditional cluster analysis, LCA models provide statistical fit indices that can be used to assess model fit and help decide on the number of classes.

The Present Study

The present study utilized LCA to empirically define victim groups throughout middle school with a large, ethnically diverse sample of over 2,000 students. Across six semesters, during the Fall and Spring of their sixth, seventh, and eighth-grade years, students reported on their experiences being victimized by their peers. Our two main objectives were to demonstrate how LCA could be used to classify students based on their peer victimization experiences and to address the debate concerning victimization types. In meeting this objective, we also addressed whether victim classes are best understood according to severity or type and whether the nature of these classes changes across the 3 years of middle school. The present LCA analyses were not designed to track changes in individual students' victimization class membership over time, but to examine whether certain patterns of victimization are consistent at different time points during middle school (i.e., structural stability).

Within this framework, we also examined the construct and predictive validity of the victimization classes yielded with LCA. Gender and perceptions of school safety were included with concurrent measures of victimization to examine the roles they play in determining victim class membership. Gender was chosen because of possible gender differences in victimization experiences depending on form of victimization (Crick & Bigbee, 1998; Paquette & Underwood, 1999). Thus, we sought to explore whether these gender differences emerged when LCA is used to derive victim groups. We utilized perceived school safety as a way of establishing the concurrent validity of our classes. In line with prior research demonstrating that victimization is positively associated with reports of feeling unsafe within school (Anderman & Kimweli, 1997; Ozer & Weinstein, 2004), we expected to see significant victim group differences in the students' perceived school safety scores. A measure of students' depressive symptoms, a known adjustment outcome resulting from victimization (Boivin, Hymel, & Bukowski, 1995), was included as a distal outcome to allow us to explore how students' depression scores one semester later varied as a function of prior victim class membership. These analyses helped to support the predictive validity of the classes. Finally, to illustrate the unique contribution of LCA in comparison to traditional cutoff scores, we compared the distribution of students assigned to victim classes based on our LCA analyses to group assignment based on cutoff scores. We also examined the predictive validity of these traditional groups in comparison to the LCA classes.

Method

Participants

Participants were 2,307 urban middle school students (45% boys, 55% girls) who took part in a 3-year (six waves) larger longitudinal study of peer relations and social adjustment during the middle school years and who had self-report data for at least one wave. Students completed surveys during the Fall and Spring semesters of their sixth, seventh, and eighth-grade years beginning in 2000. Participating students attended one of 11 public middle schools located in predominantly low Socioeconomic Status (SES) neighborhoods in the greater Los Angeles, CA area. The overall sample was ethnically diverse (44% Latino, 26% African American, 10% Asian, 9% Caucasian, 11% multiethnic).

Previously published studies on victimization that draw on this larger data set have focused exclusively on sixth-grade findings (e.g., Juvonen, Nishina, & Graham, 2006; Nishina, Juvonen, & Witkow, 2005) and primarily relied on peer reports to measure vicitimization either as a continuous variable (e.g., Bellmore, Witkow, Graham, & Juvonen, 2004; Graham et al., 2006; Nadeem & Graham, 2005) or as a categorical variable using traditional cutoffs (e.g., Graham et al., 2006; Juvonen et al., 2003). The analyses reported here are the first to incorporate all six waves of data in the longitudinal design and to examine self-reported vicitmization using a latent class approach. Participation rates for these analyses ranged between 99% and 75% for Waves 1 and 6, respectively. Our participation rate of 75% at Wave 6 is comparable to that of other longitudinal samples comprised of urban, ethnic minority adolescents (e.g., Seidman, Allen, Aber, & Mitchell et al., 1994), and exceeds the expected retention rate of 59% that takes into account average student mobility within these urban middle schools.

The exact sample size for the analyses varied from wave to wave from sixth to eighth grade. Because the implementation of the LCA strategy in this study allows for missing data on the measured outcomes using Full Information Maximum Likelihood (FIML) estimation (for more on FIML, see e.g., Enders & Bandalos, 2001), students were only eliminated if they were missing on all items of the measure (e.g., the student was absent that semester) or if they evidenced a response bias (see detailed description below). Specifically, there were 1,947 (55% girls), 1,931 (54% girls), 1,775 (54% girls), 1,723 (55% girls), 1,610 (55% girls), and 1,558 (56% girls) participants in Fall and Spring of sixth, seventh, and eighth grades, respectively.

Procedure

Students were initially recruited from their homeroom during the Fall of sixth grade and both written parent consent and student assent were obtained. Seventy-five percent of parents who were initially contacted returned completed consent forms, and of these parents, 89% provided written consent for their child to participate. At each wave, as part of a larger survey protocol conducted within a single classroom period, students completed self-report measures that included the peer victimization measure among other measures of social, psychological, and academic functioning. The survey was administered to students once each semester (i.e., every Fall and Spring) throughout their entire 3-year tenure in middle school. Approximately 24 weeks separated the administrations between Fall and Spring of one academic calendar year, and 28 weeks separated the administrations between Spring of one academic year and Fall of the next academic year. During sixth grade, the student's classroom received $5 for every completed survey to be used to benefit the classroom (e.g., classroom supplies). In subsequent years, individual students received $5 each time they completed a survey.

Measure of Victimization

At each time point, students completed a 6-item modified version of Neary and Joseph's (1994) Peer Victimization Scale. This measure was designed to be embedded in Harter's (1987) Self-Perception Profile for Children in order to reduce social desirability biases. Each item in the scale 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 first decide which type of kid is most like them and then indicate whether it is "*sort of true for me*" or "*really true for me*." That created a 4-point scale for each item with higher scores indicating higher levels of peer victimization. The original scale has two items that reflect general victimization ("picked on" and "laughed at"), one item that assesses verbal victimization ("called bad names"), and one item that assesses physical victimization ("hit and pushed around"). We added two additional items, one reflecting relational victimization ("gossiped about") and one reflecting property damage/theft ("gets their things taken or messed up"), another form of victimization relevant to large urban schools.

To ease both the analyses and the interpretation of the results yielded by the latent class analyses, we dichotomized each item such that 0 reflects a not-endorsed item (i.e., a rating of 1 or 2; more like the type of kid who does not get picked on) and 1 reflects an endorsed item (i.e., a rating of 3 or 4; more like the type of kid who does get picked on). The dichotomized responses made sense conceptually because the scale requires students to first decide to which hypothetical individual he or she is most similar. Thus, we measured whether or not the student endorsed each of the six items rather than the degree of endorsement for each item.

In preliminary analyses, we noted a unique response pattern that emerged as a separate class. Upon further investigation, this very small class appeared to represent a response bias class of students who responded on the same serial position on the page, regardless of whether the item was worded in a negative or positive direction (i.e., reverse coded). Thus, we removed students from the analyses for that wave if they evidenced this bias. Across waves, this resulted in removing 1.3% (n = 31) to 2.9% (n = 68) of the sample from a given wave.

Psychological Adjustment: Concurrent Covariates and Distal Outcomes

Perceived school safety. At each wave, 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. Alpha coefficients for this sample ranged from .73 to .83 across waves.

Depressive symptoms. The 10-item short form of the Children's Depression Inventory (Kovacs, 1992) was used to assess depressive symptoms at each wave. For each item, students were presented with three statements and asked to decide which best describes how they have been feeling in the past 2 weeks (e.g., "*I do not feel alone*," "*I feel alone often*," "*I feel alone all the time*"). Half of the items were worded in the positive direction and half in the negative direction. Items were scored on a 3-point scale (0–2) and averaged with higher scores reflecting more depressive symptoms. Alpha coefficients ranged from .80 to .85 across waves.

LCA: Data Analytic Strategy

LCA was conducted at each wave to determine victim group (i.e., class) membership based on students' responses to the six dichotomous items in the peer victimization measure. For LCA models with categorical items like those used in the study, we were interested in two types of parameters: item and class probabilities. The item probabilities are class-specific item parameters, which correspond to the probability of an individual in that specific class endorsing an item. For example, an item probability of .90 means that a student in a victim class would have a 90% probability of endorsing the item. Whereas item probabilities refer to individual items, class probabilities are parameters that describe the relative size of classes (i.e., the percentage of the sample that a given class represents).

Two basic types of class patterns can emerge from an unconstrained LCA: ordered and nonordered classes. Classes are considered "ordered" when the item probability profiles do not cross one another. That is, ordered classes are those where the probabilities for all of the items are higher for one class than the other(s). In contrast, nonordered classes are characterized by probability profiles that cross each other. This occurs when different classes are identified by one or a combination of items, rather than a high or low probability of endorsing all the items. For example, if a physical victimization class emerged, that class would be characterized by having a high likelihood of endorsing the physical victimization item but a low likelihood of endorsing the verbal and relational victimization items.

The results of LCA are based on exploratory analyses, meaning that no specific assumptions are made about the structure or distribution of classes a priori. This is analogous to an exploratory factor analysis in that there are no specific assumptions made about the number of factors or how the items relate to the underlying factor(s). LCA models are fit in a series of modeling steps, starting with the specification of a one-class model (the independence model that simply models the observed means in the data). Subsequently, the number of classes is increased until there is no further important improvement of the model. That is, there is no empirical support for additional classes because adding another class would result in very small (i.e., few students belong to the class) and/or meaningless (i.e., conceptually unclear) classes. The models for this study were run with Mplus Version 4.2 (Muthén & Muthén, 1998–2007).

The analysis accounted for the nonindependence of students nested within schools by appropriately adjusting standard errors using a sandwich estimator. The design of the study was such that students were selected to be in the study from their sixth-grade homeroom classroom. However, in seventh and eighth grades, students were not necessarily in a classroom with other study participants, making the estimation of classroom level effects difficult because we did not have enough information on classrooms to accurately estimate their effects. Accounting for the nested nature of the data at the school level allowed us to consistently control for context across the six time points of this study.

Determining model fit. With latent class models, as with structural equation modeling, there is not a single statistical indicator of good model fit. As a result, a combination of statistical indicators and substantive theory are used to decide on the best-fitting model. The four often used incidences are: the Akaike Information Criterion (AIC; Akaike, 1987), Bayesian Information Criterion (BIC; Schwartz, 1978), Adjusted BIC (ABIC; Sclove, 1987), and Consistent AIC (Bozdogan, 1987). The model that yields the smallest values on these indices indicates the best-fitting model. Additionally, likelihood-based tests are used for model comparison (e.g., chi-square difference test). Because the common likelihood ratio test cannot be used to test nested LCA models (see Lo, Mendell, & Rubin, 2001; McLachlan & Peel, 2000), we used an alterative method available in Mplus that involves bootstrapping the likelihood ratio difference to obtain a p value as described in McLachlan and Peel. This method, the Bootstrap Likelihood Ratio Test (BLRT), provides a p value that indicates which model fits best. An early simulation study examining the performance of the bootstrap for LCA models indicates that the test is a very accurate indicator of the true number of classes (Nylund, Muthén, & Asparouhov, in press). We gave the most weight to BLRT and the BIC because the AIC has been shown to be inconsistent for LCA models (Nylund et al., in press; Yang, 2006), and recent simulation studies suggest that the BLRT and BIC indices provide the most reliable indicators of true number of classes (Nylund et al., in press).

Results

The results are divided into four parts. The LCA results are presented in a methodical way, reflecting a model building and validating procedure that begins with a simple model to explore the number and structure of the victim classes and ends with the inclusion of meaningful covariates and distal outcomes to evaluate the validity of the classes. First, we provide the results of the cross-sectional latent class analyses for peer victimization separately for each semester. Second, we add the covariates, gender and perceptions of school safety, into the model and test for differences between the latent classes on these variables. Third, to establish predictive validity, we explore latent class differences in later depressive symptoms. Finally, we compare latent class assignment to two traditionally used methods for classifying individuals, raw score cutoffs and z-score cutoffs.

Cross-Sectional Latent Class Analyses

For each of the six semesters of data, cross-sectional LCA models were run by first testing a one-class model, the independence model, and then exploring models with more classes. Table 1 includes fit information (i.e., log likelihood ratio, AIC, BIC, ABIC, and p value for the BLRT) for LCA models with one through five classes. Column 1 contains the fit indices for a one-class model, column 2 for a two-class model, and so on. The values with superscripted *a* across the different columns highlight the best-fitting model (i.e., the lowest value) according to that index.

Examining the results for Fall of sixth grade in Table 1, the BIC (12265.689), ABIC (12202.148), and BLRT ($p < .001$) indicate that the three-class model fits best (see the superscripted values in column 3). This result is consistent across all six waves of analysis. Interpretation of the classes (e.g., their relative size and whether they are ordered or not) is described in the sections below where more complete models with covariates and distal outcomes are examined.

To ensure that LCA was the best way to represent peer victimization, we tried alternative latent variable models to describe the distribution and classification of victimization at each of the six waves. Specifically, we explored models which included an underlying continuous latent variable (i.e., factor analysis model), as well as more advanced hybrid latent variable models which included both a categorical and continuous latent variable (i.e., latent class factor model and a factor mixture model) (see Muthén, 2006; Muthén & Asparouhov, 2006). The results of these analyses are not detailed here for space considerations, but comparisons of these models to the LCA model indicated that there was no significant improvement in model fit or interpretation by any one of these alternative models.

Gender and Perceived School Safety Differences in Group Classification With LCA

To investigate the presence of gender and perceived school safety differences in the LCA classes,

Table 1
Fit Indices for LCA Models With 1 – 5 Classes in Fall and Spring of Sixth to Eighth Grade

No. of classes	1	2	3	4	5
No. of free parameters	6	13	20	27	34
			Fall sixth grade (N = 1947)		
Log likelihood	−7099.099	−6115.616	−6057.228	−6048.471	−6041.054
AIC	14210.198	12257.232	12154.456	12150.942	12150.109[a]
BIC	14243.567	12329.534	12265.689[a]	12301.107	12339.205
ABIC	14224.505	12288.233	12202.148[a]	12215.327	12231.186
BLRT	N/A[b]	0.000	0.000[a]	0.450	0.800
			Spring sixth grade (N = 1931)		
Log likelihood	−6693.539	−5618.920	−5563.102	−5548.451	−5537.677
AIC	13399.078	11263.840	11166.205	11150.901	11143.333[a]
BIC	13432.376	11335.985	11277.197[a]	11300.741	11332.020
ABIC	13413.314	11294.684	11213.657[a]	11214.962	11224.002
BLRT	N/A[b]	0.000	0.000[a]	0.350	0.800
			Fall seventh grade (N = 1775)		
Log likelihood	−5724.854	−4890.392	−4838.876	−4824.682	−4813.600
AIC	11461.708	9806.785	9717.751	9703.364	9695.199[a]
BIC	11494.757	9878.392	9827.916[a]	9852.086	9882.480
ABIC	11475.696	9837.091	9764.377[a]	9766.308	9774.463
BLRT	N/A[b]	0.000	0.000[a]	0.120	0.217
			Spring seventh grade (N = 1723)		
Log likelihood	−5035.646	−4253.507	−4221.843	−4209.325	−4196.191
AIC	10083.292	8533.013	8483.687	8472.651	8460.383[a]
BIC	10115.972	8603.819	8592.618[a]	8619.708	8645.566
ABIC	10096.910	8562.520	8529.080[a]	8533.932	8537.552
BLRT	N/A[b]	0.000	0.020[a]	0.188	0.400
			Fall eighth grade (N = 1610)		
Log likelihood	−4391.904	−3655.350	−3575.858	−3565.977	−3559.020
AIC	8795.809	7336.700	7191.717	7185.954[a]	7186.041
BIC	8828.079	7406.619	7299.284[a]	7331.170	7368.906
ABIC	8809.018	7365.321	7235.748[a]	7245.396	7260.895
BLRT	N/A[b]	0.000[a]	0.275	0.700	0.700
			Spring eighth grade (N = 1558)		
Log likelihood	−4070.559	−3366.944	−3314.929	−3300.948	−3296.550
AIC	8153.118	6759.888	6669.859	6655.895[a]	6661.100
BIC	8185.248	6829.503	6776.959[a]	6800.480	6843.170
ABIC	8166.187	6788.205	6713.423[a]	6714.707	6735.160
BLRT	N/A[b]	0.000	0.020[a]	0.217	1.000

Note. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT = Bootstrap Likelihood Ratio Test.
[a]Best-fitting model according to that index.
[b]BLRT not available for the one-class model.

these variables were included as covariates in the next set of analyses. Given that a three-class solution was found for each of the six waves, we added the gender and perceived school safety covariates to the three-class model. Because the model fit can change when including covariates, we also explored the two- and four-class models, but model fit indices consistently pointed to the three-class solution. We conducted a series of logistic regressions, run separately for each wave, in which the categorical latent class variable was regressed on the binary gender variable (0 = boy, 1 = girl) and the continuous perceived school safety variable. This allowed us to simultaneously examine if boys or girls were more likely to be in a certain victimization class and if students who felt safe in school were more likely to be in a certain class than students who felt unsafe in school. All of the models discussed from this point forward include gender and perceived school safety as covariates. First, we interpret the latent classes and their structure and we then present the covariate results.

Understanding the latent classes. Similar to factor analysis, it was important to consider not only the statistical indicators but also the substantive meaning of each of the classes when interpreting the results yielded with LCA. To achieve this balance, we used the model parameters to make sense of the classes and decide which model fits best. The conditional item probabilities plots for the three-class model for each of the six waves are presented in six panels in Figure 1. The item probability values are used to differentiate and add substantive meaning to the latent classes (i.e., to describe the classes). The item probabilities indicate the probability that a member of a given class would endorse the specific item. Figure 1 presents the profile plots with the six individual victimization items along the *x*-axis and the probability of endorsing the item along the *y*-axis.

Examining the results for Fall of sixth grade (upper left panel in Figure 1), Class 1 (i.e., dark diamond symbols) includes 20% of the students. This class, which represents students who strongly identified as victims, subsequently labeled the ‘‘victimized class,’’ is distinguished by having a high probability of endorsing all six of the victimization items. For instance, in Fall of sixth grade, the students in the victimized class had, on average, an 86% probability of endorsing that they had been called bad names. Class 2 (i.e., gray square symbols) reflects students who somewhat identify as victims, the ‘‘sometimes victimized class’’, which comprises 37% of the sample and had a moderate probability of endorsing the victimization items. As illustrated, this class had a 53% probability, or almost 50/50, of endorsing the ‘‘bad names’’ item. Finally, having low probability of endorsing the six items characterized Class 3 (i.e., gray triangle symbols). These students did not identify as victims (hereafter labeled the ‘‘nonvictimized class’’) and represent 43% of the sample. As illustrated, this class had a very low probability, only 8%, of endorsing the bad names item.

Similar consideration of statistical indicators as well as conceptual clarity was given at each of the

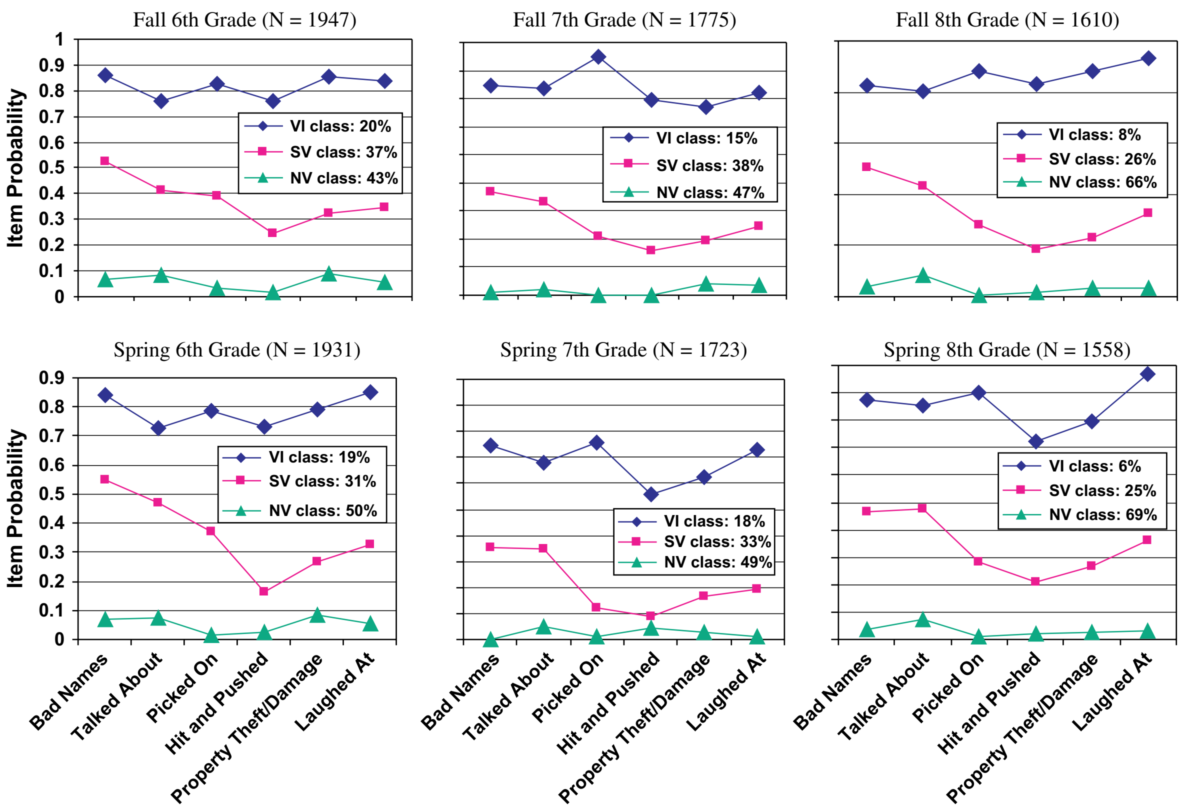

Figure 1. Conditional item probability profile plots for the three-class models for sixth through eighth grade. Class size information is presented in the legend.
Note. VI class = victimized class; SV class = sometimes victimized class; NV class = nonvictimized class.

subsequent time points (lower five panels in Table 1). Based on the independent cross-sectional analysis for each wave, a three-class model consistently provided the best fit and most meaningful solution. Moreover, the same three classes—victimized, sometimes victimized, and nonvictimized—emerged across the six time points in the study. The size of the classes (presented in the Figure 1 legends) illustrates two important observations about the relative distribution of the sample across the three classes for each of the six waves. First, at each wave, the victimized class always contained the smallest percentage of students, whereas the nonvictimized class always contained the largest percentage of students. Second, the size of the classes changed across the middle school years. The relative proportion of the victimized class decreased from 20% of the sample in Fall of sixth grade to only 6% of the sample by Spring of eighth grade. In contrast, the nonvictimized class increased in size from 43% of the sample in Fall of sixth grade to 69% of the sample in Spring of eighth grade. The sometimes victimized class decreased slightly from 37% to 25% of the sample at Fall of sixth grade and Spring of eighth grade, respectively.

Examining covariates. Table 2 presents the associations that gender and perceived school safety have with students' victimization classification across middle school. We used the nonvictimized class (i.e., Class 3) as the normative comparison group. Thus, two covariate comparisons were made: (a) the likelihood of being the victimized class compared to the nonvictimized class and (b) the likelihood of being the sometimes victimized class compared to the nonvictimized class.

The analyses for Fall of sixth grade through Fall of seventh grade (Table 2) indicate that there were no reliable gender differences for any of the classes. Girls and boys were always equally likely to be in the three victimization classes across all 3 years of middle school for these grades. However, beginning in the Spring of seventh grade and continuing through the Spring of eighth grade, there is a significant gender difference between the victimized and the nonvictimized class. The gender logistic regression coefficient (or logit) for Spring of seventh grade (-0.406, $p < .001$) for the victimized class indicates that compared to the nonvictimized class, male students are more likely to be in the victimized class than female students. This difference was not observed when comparing the sometimes victimized class and the nonvictimized class.

There also was a significant perceived school safety effect for both the victimized and sometimes victimized classes compared to the nonvictimized class. The perceived school safety logistic regression coefficient (or logit) for Fall of sixth grade (-2.172, $p < .001$) indicates that compared to the nonvictimized class, the victimized class students feel significantly less safe in school. Similarly, the logistic regression coefficient (-1.482, $p < 0.001$) for the sometimes victimized class implies that compared to the nonvictimized class, students in the sometimes victimized class feel significantly less safe in school. As portrayed in Table 2, this pattern remained consistent across middle school.

Table 2

Log Odds Coefficients and Odds Ratio for Three-Class Model With Perceived School Safety and Gender (Boys = 0, Girls = 1) as a Covariate Using the Nonvictimized Class as the Comparison Group

Class	Effect	Logit	*SE*	*t*	Odds ratio
Fall sixth grade					
Victimized	Female	−0.167	0.205	−0.813	0.846
	Safety	−2.172***	0.192	−11.298	0.114
Sometimes victimized	Female	−0.014	0.226	−0.063	0.986
	Safety	−1.482***	0.148	−9.996	0.227
Spring sixth grade					
Victimized	Female	−0.369	0.213	−1.733	0.691
	Safety	−2.175***	0.185	−11.778	0.114
Sometimes victimized	Female	0.001	0.158	0.009	1.001
	Safety	−1.422***	0.175	−8.143	0.241
Fall seventh grade					
Victimized	Female	−0.196	0.203	−0.969	0.822
	Safety	−2.609***	0.226	−11.523	0.074
Sometimes victimized	Female	0.301	0.247	1.221	1.351
	Safety	−1.926***	0.258	−7.466	0.146
Spring seventh grade					
Victimized	Female	−0.542***	0.141	−3.859	0.582
	Safety	−2.104***	0.209	−10.086	0.122
Sometimes victimized	Female	0.197	0.181	1.089	1.218
	Safety	−1.221***	0.199	−6.124	0.295
Fall eighth grade					
Victimized	Female	−0.420*	0.212	−1.983	0.657
	Safety	−1.814***	0.215	−8.42	0.163
Sometimes victimized	Female	−0.135	0.154	−0.881	0.874
	Safety	−1.073***	0.17	−6.329	0.342
Spring eighth grade					
Victimized	Female	−0.406***	0.116	−3.501	0.666
	Safety	−1.103***	0.246	−4.48	0.332
Sometimes victimized	Female	−0.038	0.278	−0.136	0.963
	Safety	−1.666**	0.231	−7.206	0.189

Note. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Predicting Differences in Depressive Symptoms Based on Group Classification With LCA

To test the predictive validity of the classes yielded with the LCA strategy, we examined whether later depressive symptoms differed across the three victimization classes. We treated depression as a distal outcome in these analyses. In other words, to examine differences between victimization classes in the Fall of sixth grade, we used students' depressive symptoms from the Spring of sixth grade. Comparisons of depressive symptoms were conducted for each of the victimization classifications yielded in the Fall of sixth through the Spring of eighth grade (i.e., five sets of analyses).

When we included depression in the model, the mean depression scores differed for each of the three classes. Evidence for victimization class differences in later depressive symptoms can be seen by the significant improvement in fit that was found between the model in which the mean depression scores were assumed equal across classes and the model in which depression scores were allowed to vary. To test which victimization groups differed in their mean depressive score, a Wald Test was conducted on all between-group comparisons. Results indicated that across all grades, the mean depressive scores were different for all groups with the exception of one comparison. As indicated in Table 3, the mean depressive score between the victimized and sometimes victimized group was not significantly different for Fall of sixth grade, but the means for both groups were different from the nonvictimized group. Thus, with the exception of the Fall of sixth grade, we concluded that there were significant differences between victimization classes in their average depression scores (see Table 3). Students in the victimized class consistently reported more subsequent depressive symptoms than those in the other two classes. Further, the depression scores were lowest for those in the nonvictimized class and in between for those in the sometimes victimized class.

Table 3
Comparison of Subsequent Depression Symptoms Based on Class Membership Utilizing LCA, Raw Score Cutoffs, and Z-Score Cutoffs Approaches

	Mean depressive symptoms		
	LCA	Raw scores	*z*-scores
Class in fall of sixth grade			
Victimized	.437[a]	.391[a]	.385[a]
Sometimes victimized	.254[b]	.306[b]	.297[b]
Nonvictimized	.176[c]	.196[c]	.196[c]
Class in spring of sixth grade			
Victimized	.399[a]	.372[a]	.374[a]
Sometimes victimized	.256[b]	.316[a]	.291[b]
Nonvictimized	.174[c]	.184[b]	.173[c]
Class in fall of seventh grade			
Victimized	.489[a]	.472[a]	.413[a]
Sometimes victimized	.292[b]	.360[b]	.319[b]
Nonvictimized	.138[c]	.190[c]	.167[c]
Class in spring of seventh grade			
Victimized	.414[a]	.423[a]	.414[a]
Sometimes victimized	.310[b]	.372[a]	.283[b]
Nonvictimized	.156[c]	.200[b]	.183[c]
Class in fall of eighth grade			
Victimized	.516[a]	.511[a]	.459[a]
Sometimes victimized	.381[a]	.372[b]	.318[b]
Nonvictimized	.180[c]	.212[c]	.180[c]

Note. For the raw-score and z-score approaches, all F statistics (range 51.12 – 79.33 for raw scores and 52.15 – 82.77 for z-scores) were significant at $p < .001$. Within each wave, mean depressive symptoms with differing subscripts within a column are significantly different from one another at $p < .001$.

Comparison of Classification Methods

In order to compare the classifications yielded by LCA to typically utilized grouping approaches, we assigned students to one of three groups (to parallel the three classes identified by the LCA models with gender and perceived school safety as covariates) using raw score and standard score cutoffs. At each wave, students' ratings on the four-point scale were averaged across their responses to all six items (αs for this sample ranged from .81 to .84 across waves). Thus, these cutoff scores described below were derived from continuous values based on composite scores (rather than individual items, as was the case for the variables utilized in the latent class analyses).

Raw scores. We chose raw score cutoff values based on the values used in the dichotomization of the originally continuous scores (1 – 4) used in the LCA. At each wave, students with average scores > 3 were labeled "victims," students with scores ≤ 2 were labeled "nonvictims," and students with scores > 2 and < 3 (i.e., everyone else in the sample) were labeled "sometimes victimized." At each wave, the largest number of students (57% – 77% of the sample) was labeled nonvictims, and the second largest group was consistently the sometimes victimized group, which comprised between 18% and 27% of the sample across waves. Victims comprised the smallest group with between 5% and 16% of the sample across waves.

Z-scores. At each wave, students' victimization scores were standardized across the entire sample. Based on their *z*-scores, students were then assigned to one of three groups at each wave. Students with *z*-scores $\geq +1$ were labeled "victims," students with *z*-scores < 0 were labeled "nonvictims," and students with *z*-scores ≥ 0 and $< +1$ (i.e., everyone else in the sample) were labeled "sometimes victimized." As with the raw score approach, at each of the six waves, the largest group was the nonvictim group (53% – 59%

of the sample). The second largest group was the sometimes victimized group, which comprised between 23% and 33% of the sample across the waves. Victims comprised the smallest group ranging between 13% and 20% of the sample.

Differences in grouping approaches. Table 4 demonstrates the overlap between the empirically derived latent classes and the two other grouping methods. The values in the cells describe the percent of overlap between two classification methods. For example, looking at the Fall of sixth grade, 75% of students classified as victims based on the LCA approach are classified as victims by raw score approach. If these two classifications methods matched perfectly, the values for corresponding classifications (i.e., victims for both approaches) would be 100%.

In comparing the two types of approaches, a pattern emerges. The raw score grouping approach does a good job at labeling nonvictims but appears to be prone to false negatives. That is, across the six waves of data, 23%–58% of students whom LCA would classify as victimized were labeled as sometimes victimized by the raw score cutoff approach. Similarly, across waves, the 29%–66% of students who were classified as sometimes victimized via LCA were labeled as nonvictims via their raw scores. The same pattern appeared to be true for the *z*-score grouping method through seventh grade. However, in eighth grade, the *z*-score method tended to produce false positives. For instance, 21%–22% of students that LCA classified as nonvictims were labeled as sometimes victimized via the *z*-score approach. Additionally, 18%–36% of students who were classified as sometimes victimized would have been considered victims via *z*-score cutoffs. One consistent finding was that each method (raw- and *z*-score cutoffs) was discrepant from the LCA results in distinguishing among the sometimes victimized students. With raw scores, many of these sometimes victimized students were considered nonvictims and with *z*-scores, sometimes victimized students were considered both victims and nonvictims.

We also compared the predictive validity of the two comparison grouping methods. One-way between-subjects analyses of variance were used to explore the ability of the raw score and *z*-score groups to predict depressive symptoms one semester later. Recall that with the LCA method, there were differences in subsequent depressive symptoms between all three classes for each semester. As illustrated in Table 4, correcting for the number of analyses run, there were significant differences between all three raw score victimization groups in only three of the five analyses. The raw score groups did not predict depressive symptoms across a grade transition (i.e., sixth to seventh grade and seventh to eighth grade). In

Table 4
LCA Victim Classes Compared With Raw Score and Z-Score Victim Groupings Across Sixth to Eighth Grade

Semester	Raw score comparison			*Z*-score comparison		
	LCA victimized (%)	LCA sometimes victimized (%)	LCA nonvictimized (%)	LCA victimized (%)	LCA sometimes victimized (%)	LCA nonvictimized (%)
Fall sixth	VI = 75	VI = 4	VI = 0	VI = 87	VI = 8	VI = 0
	SV = 25	SV = 60	SV = 2	SV = 13	SV = 56	SV = 2
	NV = 0	NV = 37	NV = 98	NV = 0	NV = 37	NV = 98
Spring sixth	VI = 69	VI = 4	VI = 0	VI = 83	VI = 8	VI = 0
	SV = 31	SV = 61	SV = 4	SV = 17	SV = 71	SV = 10
	NV = 0	NV = 35	NV = 96	NV = 0	NV = 21	NV = 90
Fall seventh	VI = 60	VI = 1	VI = 0	VI = 89	VI = 6	VI = 0
	SV = 40	SV = 42	SV = 1	SV = 11	SV = 67	SV = 13
	NV = 0	NV = 57	NV = 99	NV = 0	NV = 27	NV = 87
Spring seventh	VI = 42	VI = 2	VI = 0	VI = 87	VI = 6	VI = 0
	SV = 58	SV = 34	SV = 1	SV = 13	SV = 61	SV = 17
	NV = 0	NV = 66	NV = 99	NV = 0	NV = 33	NV = 83
Fall eighth	VI = 77	VI = 2	VI = 0	VI = 100	VI = 28	VI = 0
	SV = 23	SV = 63	SV = 2	SV = 1	SV = 62	SV = 21
	NV = 0	NV = 35	NV = 98	NV = 0	NV = 10	NV = 79
Spring eighth	VI = 73	VI = 3	VI = 0	VI = 100	VI = 36	VI = 0
	SV = 27	SV = 68	SV = 4	SV = 0	SV = 57	SV = 22
	NV = 0	NV = 29	NV = 96	NV = 0	NV = 8	NV = 78

Note. VI = victims; SV = sometimes victimized; NV = nonvictims.

contrast, there were significant differences between the *z*-score groups in predicting depressive symptoms across all semesters. However, it is important to note that compared to both the raw score and *z*-score groups, there was a wider spread between the LCA victimization classes in subsequent depression. For example, in Fall of sixth grade, the differences between the victimized and nonvictimized groups in Spring of sixth-grade depression was .261 for LCA classes (.437−.176), .195 for raw score groups (.391−.196), and only .189 for the *z*-score groups (.385−.196). This trend continues across middle school.

Discussion

The goals of the present study were to explore the nature of middle school victimization while providing an illustrative example of LCA as an alternative method for classification. In so doing, we generated answers to two substantive research questions about peer victimization. First, we established that victim groups are best understood according to severity rather than type during the middle school years. Second, we found that there was consistency in the class structure across the 3 years of middle school suggesting three (instead of two) distinct groups: victimized, sometimes victimized, and nonvictimized. Moreover, there was a consistent trend such that a smaller proportion of students reported being victimized in the later years of middle school compared to the earlier years. We also demonstrated the validity of LCA when we found meaningful class differences for students' concurrent perceptions of school safety and later depressive symptoms.

Victimization Classes Based on Frequency, Not Type

Previous studies have classified students into groups based on theoretically based assumptions about the importance of victimization types or where cutoff values should be placed (e.g., Olweus, 1993a; Perry et al., 1988). Because latent class analyses are exploratory in nature and empirically driven, they provide latent variables that best describe the data without model specifications that promote a specific pattern of results. In this study, we relied on the students' own reports to inform us about the most relevant distinctions. Starting in Fall of sixth grade, we found support for a three-class model in which the classes were "ordered." That is, the students in the victimized class had a high probability of endorsing each of six victimization items, the sometimes victimized class had approximately a 50/50 probability of endorsing any given victimization item, and the nonvictimized class was characterized by having a very low probability of endorsing each of the six items.

In contrast, nonordered classes, which were not supported in the present study, would be characterized by class profiles in which not all of the items distinguished between classes in the same manner. For example, if nonordered classes were to emerge in the analysis of the victimization items, the classes might have been distinguished by type of victimization versus severity. In this context, severity is defined in terms of probability of endorsing all the items. The failure to find support for nonordered classes based on victimization type is consistent with previous research finding high reliability among victimization items—both when measured by peer nominations (Bellmore & Cillessen, 2006) and self-report (Ladd & Kochenderfer-Ladd, 2002). These ordered classes could be capturing an underlying continuum of victimization that a one-factor model would find, but LCA provides the classification into the victimization classes that are valuable for important comparisons with other variables.

In our assessment of different grouping methods, we found differences in the LCA classifications compared to groups based on raw scores or standardized scores. Compared to the LCA classes, the raw score cutoffs tended to underestimate students being in the more frequently victimized classes, whereas *z*-score cutoffs overestimated students being in the more frequently victimized classes. The discrepancy between the empirically driven (LCA) classes and subjectively derived classes (cutoffs) increased over time, when students' overall reports of victimization decreased. Thus, in addition to being unable to empirically determine both the appropriate number of victim classes to describe a population and whether the victim classes are distinguished by type or by severity, predetermined cutoffs employ presumptions about the developmental nature of peer victimization that may be inappropriate. That is, the same cutoff scores are typically used to form victim groups, without taking into consideration developmental changes in the prevalence of victimization that may affect group formation.

When comparing the predictive validity of the LCA approach to the raw score and *z*-score groupings, we found that LCA classes were better at predicting depressive symptoms than raw scores and equally good at predicting subsequent depressive symptoms as the *z*-score groupings. However, in all cases, the LCA classes yielded a wider range in subsequent depression scores than both the raw- and *z*-score groupings.

Developmental Consistency in Victimization Class Structure

We were also able to assess the latent classes that emerged at multiple time points. The goal of these multiple analyses was not to track changes in students' victimization class membership over time but rather to establish whether the construct of victimization remains stable developmentally. This is important for determining whether certain behaviors are more prototypical of victimization at different ages. Over the course of middle school, we found structural stability in the latent victimization construct. The three-class model that included a victimized class, a sometimes victimized class, and a nonvictimized class of students was independently replicated at all six time points. Thus, it does not appear that, at least across the middle school years, students make distinctions between different types of victimization; rather, they make distinctions in the degree to which they experience peer victimization.

That the empirical findings do not support classifying students based on victimization type suggests that students do not tend to view themselves as solely relational victims or only victims of physical harassment. Students who experience one type are likely to be experiencing other types, which may explain why the targets of different forms of peer victimization report experiencing similar magnitudes of psychological distress (see Nishina & Juvonen, 2005). What would be interesting for future research would be to investigate whether similar patterns are found for adolescents when peer-reported victimization is examined with LCA. That is, do students have reputations as victims of predominantly one form of harassment or do they have reputations as victims of both direct and indirect harassment?

The Victimized Class Shrinks During Middle School

In examining the relative representation of each of the three victimization classes, we found that in Fall of sixth grade, the victimized class represented almost one fifth of the sample and the remainder of the students were somewhat evenly distributed between the sometimes victimized class (37%) and the nonvictimized class (46%). Thus, at the beginning of middle school, over half of the sample appeared to be experiencing at least some peer victimization at school. This finding is consistent with previous cross-sectional research conducted with U.S. adolescents (e.g., Nansel et al., 2001) and daily reports of victimization experiences (Nishina & Juvonen, 2005). Sixth-grade students may be particularly vulnerable to being targeted for several reasons. In Fall of sixth grade, the students in our study were the youngest students in the school. Moreover, the Fall data were collected close to the beginning of the year when students would have been acclimating to a new school environment—for example, compartmentalized school day structure versus self-contained classrooms, larger student body, new peers, the potential loss of elementary school friends, and so on (see Eccles & Midgley, 1989). These new challenges and demands, coupled with the likelihood that these students were physically smaller than their older schoolmates, may have made students in sixth grade easy targets both physically (see Hodges & Perry, 1999) and psychologically (see Egan & Perry, 1998).

Despite a relatively high proportion of students classified into a class that reflected at least occasional peer victimization experiences shortly after the transition to middle school, both groups got considerably smaller over time. By the end of eighth grade, three quarters of students viewed themselves as nonvictimized and only 6% of the sample viewed themselves as victimized (see also Nansel et al., 2001). Thus, it appears that across the middle school years, overall, students experience a decline in victimization. This decline may occur for a variety of reasons. Smith et al. (1999) have reported that decreases in reported peer victimization are due to decreases in bullying by older peers. Students may be more physically developed and therefore make less easy targets. They may also have developed social skills to avoid victimization or to entertain alternative interpretations for seemingly aggressive behavior (Smith et al., 1999). The development of these skills may make older adolescents less psychologically vulnerable to victimization as well.

It is also possible that the shrinking victimized class is merely due to the victimized students being more likely to drop out of the study. To test this possibility, we conducted a chi-square analysis to test whether students in the victimized class at Wave 1 were more likely to have dropped out of the study by Wave 6 than students in the sometimes or nonvictimized classes. Our analyses comparing the number of students in each victim class who remained in the study to those who dropped out of the study by Wave 6 yielded a significant chi-square: $\chi^2(2) = 22.25$, $p < .001$. Comparing observed to expected frequencies, we found that students who dropped out of the study were no more or less likely than expected to be in the victimized class ($Z = 1.2$). However, those who dropped out were more likely than expected to be in the sometimes victimized class ($Z = 2.3$) and less likely than expected to be in the nonvictimized class ($Z = -2.9$). Thus, although the shrinking size of the somewhat victimized class may be partially due to attrition in our study, attrition does not solely explain the reduction in the size of the victimized class.

Victimization Status, Perceived School Safety and Depression Differences

We considered gender and perceived school safety as covariates and depression as a distal outcome because of prior evidence of their consistent association with peer victimization (Anderman & Kimweli, 1997; Boivin et al., 1995; Crick et al., 2002). When examining gender in assignment to victimization class, we found that early in middle school there were no gender differences in the likelihood of being categorized in any of the victimized classes. However, starting in the Spring of seventh grade, we found that boys were more likely than girls to be in the victimized class compared to the nonvictimized class. Thus, boys and girls appear to be equally likely to report experiencing a variety of types of victimization during the early part of middle school, but girls are less likely to be in the victimized class later on. We also observed differences in our second covariate, perceived school safety, based on victimization class. For perceptions of school safety, when students were personally experiencing victimization, they viewed their school environment as a whole to be an unsafe place. These combined personal experiences and perceptions may explain the strong evidence for a host of maladjustment indicators that have been found to coincide with and follow experiences of victimization (see Juvonen & Graham, 2001).

Our findings also revealed class differences in subsequent reports of depressive symptoms. We consistently found that students in the victimized class reported the most depressive symptoms one semester later. This finding is consistent with studies examining social stress and depression (Boivin et al., 1995). What is beneficial about the LCA approach is that we were able to test both covariates and the distal outcomes simultaneously in a single model.

Limitations

One limitation of the present study is that we only collected data during the middle school years. As such, we do not know whether these findings would be replicated with different age groups. For example, it might be reasonable to expect that in high school, a similar pattern emerges, with a relatively high percentage of ninth graders (the youngest students in the high school) being classified into the two victimized groups, with declines in the victimized and sometimes victimized classes as students acclimate to their new school environment. But overall, we would expect to see smaller percentages of students reporting that they are victimized than exists during the middle school years.

A second limitation of our study is that we may not have included all of the relevant subtypes of peer victimization in our measure. It is not yet known whether the distinction between physical versus verbal versus relational victimization is more valid than distinguishing between more specific subtypes of aggression. For example, because we included only one item to capture relational victimization, gossiped about, the most frequently experienced form of relational victimization in early adolescence (Paquette & Underwood, 1999), we could not distinguish between different experiences of relational victimization including being gossiped about, being ignored, and/or being excluded. Based on the consistent results of the present study, it seems unlikely that victim classes would emerge based on type of victimization. However, to eliminate these concerns, LCA models that include many items and many more forms of victimization should be evaluated (Underwood et al., 2001).

Although the application of exploratory LCA in this study identified meaningful victimization groups, it is not to say that LCA is the single best classification method across all settings. Whether LCA or cut points are more useful depends on the question of interest. Often, classifications are used to compare extreme ends of a population (e.g., depressed versus nondepressed). But when LCA is applied in an exploratory fashion without a priori restrictions on the number and type of classes that will emerge, the results of the LCA may not yield the classifications of interest for such comparisons. Thus, if the goal is to compare individuals in predetermined groupings, LCA may not provide the most useful classifications.

Future Directions

The goal of the present study was to empirically establish what victimization classes exist among students during early adolescence. We view the analyses presented in this paper as making important stand-alone contributions to the understanding of peer victimization. For example, we found three ordered latent classes for peer victimization that are based on victimization frequency/severity rather than form of victimization. These three classes independently emerged both in Fall and in Spring across the students' middle school years and when covariates and distal outcomes were included.

An important next step will be to track trends in individual students' class membership over time. That is, are students more likely to move from more severe to less severe classes or vice versa? Based on the relative size of the classes presented in Figure 1, we can generate a few hypotheses about the movement of individual students over time in terms of their victim class membership. Specifically, it appears that if a student moves from one class to another, that student is most likely going to change into a class with less severe victimization. Thus, it might be important to explore the conditions under which individual students move against the trend of less victimization. That is, what characteristics are associated with students who move from a lower to a higher victimized class? Additionally, specific predictor and distal outcome variables could be added to the model to predict groups of students who are at risk for the most negative outcomes. Students who are chronically classified as victimized or who become classified as victimized during their middle school careers may be at risk for the most significant psychosocial maladjustment, whereas students who start out as victimized, but later become nonvictimized, may exhibit relative resilience (cf. Juvonen, Nishina, & Graham, 2000; Olweus, 1993b).

Detecting which students are most at risk has important practical implications for the effectiveness of both treatment and prevention efforts. By reliably establishing which victimization classes exist, who comprises the classes, and on what adjustment indices the classes differ, interventions can be tailored to address the needs of specific students. Thus, the latent class analyses presented in this paper can yield relatively error-free, unbiased information about the heterogeneity of social development that can be used to inform both theory and practice.

References

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, *52*, 317–332.

Anderman, E. M., & Kimweli, D. M. S. (1997). Victimization and safety in schools serving early adolescents. *Journal of Early Adolescence*, *17*, 408–438.

Archer, J., & Coyne, S. M. (2005). An integrated review of indirect, relational, and social aggression. *Personality and Social Psychology Review*, *9*, 212–230.

Bellmore, A. D., & Cillessen, A. H. N. (2006). Reciprocal influences of victimization, perceived social preference, and self-concept in adolescence. *Self and Identity*, *5*, 209–229.

Bellmore, A. D., Witkow, M. R., Graham, S., & Juvonen, J. (2004). Beyond the individual: The impact of ethnic context and classroom behavioral norms on victims' adjustment. *Developmental Psychology*, *40*, 1159–1172.

Boivin, M., Hymel, S., & Bukowski, W. M. (1995). The roles of social withdrawal, peer rejection and victimization by peers in predicting loneliness and depressed mood in childhood. *Development and Psychopathology*, *7*, 765–785.

Boivin, M., Hymel, S., & Hodges, E. V. E. (2001). Toward a process view of peer rejection and harassment. In J. Juvonen & S. Graham (Eds.), *Peer harassment in school: The plight of the vulnerable and victimized* (pp. 265–289). New York: Guilford Press.

Bozdogan, H. (1987). Model selection and Akaike's Information Criterion (AIC): The general theory and its analytical extensions. *Psychometrika*, *52*, 345–370.

Clogg, C. C. (1988). Latent class models for measuring. In R. Langeheine, & J. Rost (Eds.), *Latent trait and latent class models* (pp. 173–205). New York: Plenum Press.

Crick, N. R., & Bigbee, M. A. (1998). Relational and overt forms of peer victimization: A multiinformant approach. *Journal of Consulting and Clinical Psychology*, *66*, 337–347.

Crick, N. R., Casas, J. F., & Nelson, D. A. (2002). Toward a more comprehensive understanding of peer maltreatment: Studies of relational victimization. *Current Directions in Psychological Science*, *11*, 98–101.

Eccles, J. S., & Midgley, C. (1989). Stage/environment fit: Developmentally appropriate classrooms for early adolescents. In R. Ames & C. Ames (Eds.), *Research on motivation in education* (*Vol. 3*, pp. 139–186). San Diego, CA: Academic Press.

Egan, S. K., & Perry, D. G. (1998). Does low self-regard invite victimization? *Developmental Psychology*, *34*, 299–309.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *8*, 430–457.

Gottfredson, G. (1984). *Effective school battery*. Odessa, FL: Psychological Assessment Resources.

Graham, S., Bellmore, A., & Mize, J. (2006). Aggression, victimization, and their co-occurrence in middle school. *Journal of Abnormal Child Psychology*, *34*, 363–378.

Graham, S., & Juvonen, J. (1998). Self-blame and peer victimization in middle school: An attributional analysis. *Developmental Psychology*, *34*, 587–599.

Harter, S. (1987). *Manual for the self-perception profile for children*. Denver, CO: University of Denver.

Hodges, E. V. E., & Perry, D. G. (1999). Personal and interpersonal antecedents and consequences of victimization by peers. *Journal of Personality and Social Psychology*, *76*, 677–685.

Juvonen, J., & Graham, S. (2001). *Peer harassment in school: The plight of the vulnerable and victimized*. New York: Guilford Press.

Juvonen, J., Graham, S., & Schuster, M. (2003). Bullying among young adolescents: The strong, the weak, and the troubled. *Pediatrics*, *112*, 1231 – 1237.

Juvonen, J., Nishina, A., & Graham, S. (2000). Peer harassment, psychological adjustment, and school functioning in early adolescence. *Journal of Educational Psychology*, *92*, 349 – 359.

Juvonen, J., Nishina, A., & Graham, S. (2006). Ethnic diversity and perceptions of safety in urban middle schools. *Psychological Science*, *17*, 393 – 400.

Kaufman, P., Chen, X., Choy, S. P., Ruddy, S. A., Miller, A. K., Chandler, K. A., et al. (1999). *Indicators of school crime and safety* (NCES 1999-057/NCJ-178906). Washington, DC: Departments of Education and Justice.

Kovacs, M. (1992). *Children's depression inventory*. North Tonawanda, NY: Multi-Health Systems.

Ladd, G. W., & Kochenderfer-Ladd, B. (2002). Identifying victims of peer aggression from early to middle childhood: Analysis of cross-informant data for concordance, estimation of relational adjustment, prevalence of victimization, and characteristics of identified victims. *Psychological Assessment*, *14*, 74 – 96.

Lazarsfeld, P. F., & Henry, N. W. (1968). *Latent structure analysis*. New York: Houghton Mifflin.

Little, T. D., Jones, S. M., Henrich, C. C., & Hawley, P. H. (2003). Disentangling the ''whys'' from the ''whats'' of aggressive behavior. *International Journal of Behavioral Development*, *27*, 122 – 133.

Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*, 767 – 778.

Magnusson, D., & Cairns, R. B. (1996). Developmental science: Toward a unified framework. In R. B. Cairns & G. H. Jr. Elder (Eds.), *Developmental science. Cambridge studies in social and emotional development* (pp. 7 – 30). New York: Cambridge University Press.

McCutcheon, A. L. (1987). *Latent class analysis*. Beverly Hills, CA: Sage Publications.

McLachlan, G. J., & Peel, D. (2000). *Finite mixture models*. New York: John Wiley.

Muthén, B. (2006). Should substance use disorders be considered as categorical or dimensional? *Addiction*, *101* (Suppl. 1), 6 – 16.

Muthén, B., & Asparouhov, T. (2006). Item response mixture modeling: Application to tobacco dependence criteria. *Addictive Behaviors*, *31*, 1050 – 1066.

Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analysis. Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, *24*, 882 – 891.

Muthén, L. K., & Muthén B. (1998 – 2007). *Mplus user's guide* (4th ed.). Los Angeles: Muthén & Muthén.

Mynard, H. M., & Joseph, S. (2000). Development of the multidimensional peer-victimization scale. *Aggressive Behavior*, *26*, 169 – 178.

Nadeem, E., & Graham, S. (2005). Early puberty, peer victimization, and internalizing symptoms in ethnic minority adolescents. *Journal of Early Adolescence*, *25*, 197 – 222.

Nansel, T. R., Overpeck, M., Pilla, R. S., Ruan, W. J., Simons-Morton, B., & Scheidt, P. (2001). Bullying behaviors among US youth: Prevalence and association with psychosocial adjustment. *Journal of the American Medical Association*, *285*, 2094 – 2100.

Neary, A., & Joseph, S. (1994). Peer victimization and its relationship to self-concept and depression among schoolgirls. *Personality and Individual Differences*, *16*, 183 – 186.

Nishina, A., & Juvonen, J. (2005). Daily reports of witnessing and experiencing peer harassment in middle school. *Child Development*, *76*, 435 – 450.

Nishina, A., Juvonen, J., & Witkow M. (2005). Sticks and stones may break my bones, but names will make me sick: The consequences of peer harassment. *Journal of Clinical Child and Adolescent Psychology*, *34*, 37 – 48.

Nylund, K., Muthén, B., & Asparouhov, T. (in press). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*.

Olweus, D. (1993a). *Bullying at school: What we know and what we can do*. Oxford, UK: Blackwell.

Olweus, D. (1993b). Victimization by peers: Antecedents and long-term outcomes. In K. H. Rubin, & J. B. Asendorpf (Eds.), *Social withdrawal, inhibition, and shyness in childhood* (pp. 315 – 341). Hillsdale, NJ: Lawrence Erlbaum Associates.

Ozer, E. J., & Weinsten, R. S. (2004). Urban adolescents' exposure to community violence: The role of support, school safety, and social constrains in a school-based sample of boys and girls. *Journal of Clinical Child and Adolescent Psychology*, *33*, 463 – 476.

Paquette, J. A., & Underwood, M. K. (1999). Gender differences in young adolescents' experiences of peer victimization: Social and physical aggression. *Merrill-Palmer Quarterly*, *45*, 242 – 266.

Perry, D. G., Kusel, S. J., & Perry, L. C. (1988). Victims of peer aggression. *Developmental Psychology*, *24*, 807 – 814.

Schwartz, D. (2000). Subtypes of victims and aggressors in children's peer groups. *Journal of Abnormal Child Psychology*, *28*, 181 – 192.

Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*, 461 – 464.

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, *52*, 333 – 343.

Seidman, E., Allen, L., Aber, J. L., Mitchell, C., & Feinman, J. (1994). The impact of school transitions in early adolescence on the self-system and perceived social context of poor urban youth. *Child Development*, *65*, 507 – 522.

Smith, P. K., Cowie, H., Olafsson, R. F., & Liefooghe, A. P. D. (2002). Definitions of bullying: A comparison of terms used, and age and gender differences, in a fourteen-country international comparison. *Child Development*, *73*, 1119 – 1133.

Smith, P. K., Madsen, K. C., & Moody, J. C. (1999). What causes the age decline in reports of being bullied at school? Towards a developmental analysis of risks of being bullied. *Educational Research*, *41*, 267–285.

Solberg, M. E., & Olweus, D. (2003). Prevalence estimation of school bullying with the Olweus Bully/Victim Questionnaire. *Aggressive Behavior*, *29*, 239–268.

Storch, E. A., Nock, M. K., Masia-Warner, C., & Barlas, M. E. (2003). Peer victimization and social-psychological adjustment in Hispanic and African-American children. *Journal of Child and Family Studies*, *12*, 439–452.

Underwood, M. K., Galen, B. R., & Paquette, J. A. (2001). Top ten challenges for understanding gender and aggression in children: Why can't we all just get along? *Social Development*, *10*, 248–266.

Yang, C. (2006). Evaluating latent class analyses in qualitative phenotype identification. *Computational Statistics & Data Analysis*, *50*, 1090–1104.