A Finite Mixture Model of Growth Trajectories of Adolescent Alcohol Use: Predictors and Consequences

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The current study sought to identify classes of growth trajectories of adolescent alcohol use and to examine the predictors and outcomes associated with the classes. Alcohol use was assessed from Grades 7 to 12 in a school-based sample. Latent growth mixture modeling was used, and results indicated 5 discrete longitudinal drinking patterns. The 2 most common drinking patterns included occasional very light drinking from Grades 7 to 12 and moderate escalation in both quantity and frequency of alcohol use. One group drank infrequently but at high levels throughout the study period. Another group exhibited rapid escalation in both quantity and frequency. The final group started at high levels of frequency and quantity in Grade 7 and showed rapid de-escalation in frequency. Emotional distress and risk taking distinguished the classes, and all classes, particularly rapid escalators, showed elevated levels of alcohol-related problems relative to occasional very light drinkers.

Considerable data suggest heterogeneity in how alcohol use changes during adolescence (e.g., Stice, Myers, & Brown, 1998; Wills, McNamara, Vaccaro, & Hirkry, 1996). Describing heterogeneity and examining antecedents and consequences of different drinking trajectories will lead to more-informative etiological models. One way to advance these goals is by using person-centered approaches (e.g., cluster analysis), which involve identifying homogeneous subgroups that share a common profile or configuration on several factors of interest (e.g., Cicchetti & Rogosch, 1996; Magnusson & Bergman, 1990). In contrast to person-centered approaches, most studies of adolescent alcohol use apply variable-centered approaches (e.g., regression analysis), which focus on relationships between variables. An advantage of person-centered approaches is that they can elucidate a variety of time-dependent patterns of behavior and multiple pathways to diverse outcomes (Cicchetti & Rogosch, 1996; Lease & Ollendick, 1993). Understanding etiological pathways to adolescent alcohol use may help identify potential targets, timing, and content for preventive interventions (Glantz & Leshner, 2000). In the current article, subgroups of adolescents were identified on the basis of shared growth trajectories of quantity and frequency of alcohol use, and predictors and consequences of the growth trajectories were examined using latent growth mixture modeling (LGMMing).

Common person-centered strategies used to characterize heterogeneity in longitudinal patterns of adolescent alcohol and drug use include a priori and cluster-analytic approaches. Stice et al. (1998) used an a priori approach to identify longitudinal patterns of frequency of adolescent alcohol use. They identified three stable patterns of alcohol use (stable abstainers, stable moderate drinkers, and stable heavy drinkers) and two escalation patterns (escalation to moderate and to heavy levels of drinking). A more empirical approach was taken by Wills et al. (1996), who used cluster analysis to identify five groups of adolescents on the basis of common longitudinal patterns of frequency of substance use (a composite of alcohol, cigarette, and marijuana use). The groups identified included stable abstainers, minimal experimenters (very infrequent use over the study period), late starters (infrequent use in Grades 7 and 8 followed by escalation from Grade 8 to 9), and two groups of escalators (early onset with moderate or rapid escalation).

These longitudinal grouping approaches demonstrate heterogeneity in how adolescent alcohol and drug use unfolds over time. However, one limitation of a priori and cluster-analytic longitudinal grouping studies is that they are limited to one dimension of alcohol use (e.g., frequency). Adolescent alcohol use is a multidimensional phenomenon that includes quantity, frequency, and alcohol-related problems (e.g., Bailey & Rachal, 1993; White, 1987). Examining just one dimension provides an incomplete picture of the phenomenon. A common alternative to examining
one dimension is to combine quantity and frequency (by multiplying the two variables) into one intensity variable. However, this approach may obscure important patterns of alcohol use. For example, when combining quantity and frequency, it is hard to distinguish low-frequency heavy drinking (or occasional binge drinking) from frequent moderate drinking. This is problematic because these two drinking patterns may be associated with different etiological pathways and may have different impacts on achieving developmental tasks. Some data suggest different correlates of quantity and frequency of alcohol use (Lee, Green, & Oei, 1999). Moreover, quantity and frequency may change at different rates, and combining these dimensions of alcohol use might obscure the difference. In sum, it may be important to distinguish between trajectories of quantity and frequency of alcohol use.

Another limitation of a priori and cluster-analytic approaches is that classification is assumed to be perfectly reliable, which is probably untenable. Groups based on longitudinal patterns of alcohol use are likely to have fuzzy boundaries. Such ambiguity in classification can produce poorly defined groups that are difficult to replicate and may lead to erroneous conclusions about their antecedents and consequences. The current article addresses these limitations by modeling growth in both quantity and frequency of alcohol use using LGMMing, which is a general form of growth modeling, with the addition of an unobserved categorical variable. Applications of LGMMing are still uncommon in the literature, so we introduce this approach by first describing conventional latent growth modeling.

Conventional latent growth modeling has become a common way of modeling individual differences in growth in an outcome, such as substance use (e.g., Duncan & Duncan, 1996; Wills & Cleary, 1999). In these models, the underlying growth process is conceptualized as continuous and expressed in latent growth factor means and variances. The growth factor means represent the average growth trajectory in the sample, and the variance around these means represents heterogeneity or individual differences in growth. In addition to means and variances of the latent growth factors, the relation of the growth factors to other variables is of interest.

LGMMing expresses growth heterogeneity differently—in a discrete rather than a continuous fashion—by identifying discrete classes or mixtures to distinguish homogenous subgroups of individuals on the basis of common patterns of growth. This is accomplished by adding a latent categorical variable where each latent class is allowed to have its own model of growth, thereby defining latent classes on the basis of different patterns of change (B. Muthén & Shedden, 1999). The probability of membership in each class for each individual is estimated, therefore unreliability of classification is taken into account. Variances and covariances of growth factors within each class can also be estimated to allow for within-class heterogeneity.

LGMMing has not been widely used in the adolescent substance use literature. To our knowledge, only B. Muthén and colleagues (B. Muthén & Muthén, 2000; B. Muthén & Shedden, 1999) and Li, Duncan, and Hops (2001) have previously used LGMMing with repeated measures alcohol use data. B. Muthén and Shedden (1999) identified three latent classes on the basis of heavy drinking trajectories in early adulthood (ages 18–24 years), and B. Muthén and Muthén (2000) found four latent trajectory classes when they extended their panel data to age 30. In both articles, one latent class, characterized by rapid acceleration in heavy drinking, was at increased risk for future alcohol dependence. Li et al. (2001) followed an adolescent sample from Grade 6 to Grade 12 and identified two latent classes on the basis of growth trajectories of frequency of alcohol use. One class was characterized by high initial frequency of alcohol use with accelerated growth in high school. The other class was characterized by low initial frequency with accelerated growth in both middle school and high school. The high initial status group showed the greatest continuity of substance use in late adolescence and young adulthood. These studies demonstrated that heterogeneity in longitudinal patterns of alcohol use can be described by latent classes and suggest that alcohol-related problems may be linked to specific trajectories of drinking.

Similar to these studies, we used LGMMing to examine growth in adolescent alcohol use from Grade 7 to Grade 12 and relationships between trajectories and other variables (psychosocial risk factors and alcohol-related problems). We extend previous research in three ways. First, we simultaneously modeled growth trajectories of both quantity and frequency of alcohol to identify latent classes. This allows examination of the course with which quantity and frequency of alcohol use unfolds during adolescence and of how these developmental trajectories presage the experience of alcohol-related problems. For example, it is possible that early onset with rapid escalation may be an especially problematic pattern that serves as a precursor to alcohol-related problems. Alternatively, it is possible that developmental trajectories are unimportant, and instead, the critical factor associated with alcohol-related problems may be levels of drinking at a given time. Second, we used a larger sample than that used by Li et al. (2001; $N = 1,918$ vs. $N = 171$). Thus, we are likely to identify a greater variety of growth trajectories of adolescent alcohol use, and our class definitions are likely to be more reliable and stable. Finally, we demonstrate how predictors of latent classes can be incorporated in LGMMing, which enables one to examine whether the correlates of different trajectories are shared or unique. This is important because it might suggest etiological processes that are unique to some patterns of adolescent alcohol use.

Reviews suggest that alcohol use has many determinants and that individual differences including disinhibition (e.g., risk taking, aggression, impulsivity) and emotional distress play a role in the development of adolescent alcohol use (Hawkins, Catalano, & Miller, 1992; Petraitis, Flay, & Miller, 1995). We examined risk taking (an expression of disinhibition; see Windle, 1990) and emotional distress as predictors of alcohol use trajectories because these variables are linked to two primary mechanisms of alcohol use—positive and negative reinforcement (Cox & Klinger, 1988; Pihl & Peterson, 1995). High risk taking was expected to be associated with rapid escalation in both quantity and frequency of alcohol use because after initiation these adolescents would find the positive reinforcement effects of alcohol (i.e., enhancement of positive affect) particularly appealing. Also, after initiating drinking, adolescents who experience high levels of emotional distress were expected to show rapid escalation in both their quantity and frequency of alcohol use because they would find the negative reinforcement effects of alcohol (i.e., alleviation of negative affect) particularly appealing.
Sample

The sample was drawn from the no-treatment control condition of the Television, School, and Family Smoking Prevention and Cessation Project (Flay et al., 1995). Excluding 23 adolescents (1.2%) who did not provide any quantity or frequency of alcohol use data resulted in a sample of 1,918 adolescents who were surveyed in April of 1986, 1987, 1988, and 1991 when they were in Grades 7, 8, 9, and 12. The ethnic breakdown was 41.8% Hispanic, 32.2% White, 9.6% Asian, 10.4% Black, and 5.9% self-identified as another ethnicity. Fifty-two percent were female.

Current LGMM as implemented in MPlus Version 2.01 (L. K. Muthén & Muthén, 2001) allows missing data on binary and ordered categorical latent class indicators (here alcohol-related negative consequences) and continuous observed outcomes (here repeated measures of quantity and frequency of alcohol use) and assumes the data are missing at random (MAR; Little & Rubin, 1989). MAR assumes that unmeasured covariates related to missingness are unrelated to variables critical to this study. We compared cases with complete data with those with missing data on quantity and frequency of alcohol use at each wave and on alcohol-related problems. Using an alpha level of .01 to adjust for multiple tests, we found that missingness was not significantly associated with any of these outcomes. We also determined that variables thought to predict alcohol use (risk taking and emotional distress) were not associated with missingness, suggesting that assuming MAR for missing outcome data is reasonable.

Procedure

Trained data collectors provided standard instructions and administered the questionnaires in classrooms. All data were based on adolescent self-report.

Alcohol use. At each wave, adolescents reported frequency of use in terms of the number of days in the past month that they drank alcohol. Responses ranged from 0 to 30 days. Quantity of alcohol use was assessed with one item, “When you drink alcohol, how many drinks do you usually have?” Response choices were 0 (I don’t drink), 1 (one or less), 2 (two drinks), 3 (three–five drinks), and 4 (six or more).

Alcohol-related problems. To examine the potential effect of growth trajectories on alcohol-related problems in late adolescence, we assessed alcohol-related negative consequences in Grade 12. Adolescents responded yes or no to five items that assessed alcohol-related problems in the past year, including trouble at home, trouble at school or work, trouble with police, received counseling or therapy, and trips to the emergency room. These items were summed.

Predictors. Psychosocial predictors included emotional distress and risk taking, which were assessed in Grades 7, 8, 9, and 12. Adolescents responded to four emotional distress items (e.g., felt nervous and stressed) using a 4-point scale to describe the frequency of distressed feelings (1 = never to 4 = often). Unstandardized Cronbach’s alpha at each assessment period ranged from .78 to .84. Risk taking was assessed with three items (e.g., “I like to take risks”). Adolescents used a 5-point response scale to describe how well each item described them (1 = not at all to 5 = very well). Unstandardized Cronbach’s alphas ranged from .81 to .84. A scale score for emotional distress and risk taking at each assessment period was formed by averaging items. Previous research has found these scales to predict outcome as expected (Landrine, Richardson, Klonoff, & Flay, 1994; Simon, Richardson, Dent, Chou, & Flay, 1998).

Confirmatory factor analysis was used to evaluate whether the scale scores at each assessment could be combined to form dispositional measures. Two latent factors were specified, with one indicated by measures of risk taking and the other by measures of emotional distress. The latent factors were free to covary, and each item was constrained to load on only one factor. The residual variances were freely estimated and were auto-correlated. This model showed an adequate fit to the data, \( \chi^2(15, N = 1,814) = 35.79, p \leq .05 \) (comparative fit index [CFI] = .99, root-mean-square error of approximation [RMSEA] = .03). The factors were moderately correlated (r = .38, p < .01), such that high levels of risk taking were associated with high levels of emotional distress. The indicators were averaged for subsequent analysis. High scores suggest a tendency to experience high levels of emotional distress or risk taking over the study period.

Results

Our goal was to identify classes of adolescents on the basis of longitudinal patterns of quantity and frequency of alcohol use. This was done in two steps. First, discrete classes of growth trajectories were identified separately for quantity and frequency of alcohol use. We refer to this analysis as single-domain latent growth mixture analysis. Second, after establishing the number of classes of quantity and frequency trajectories, we modeled latent classes on the basis of both quantity and frequency growth trajectories. We refer to this analysis as two-domain latent growth mixture analysis.

Finally, after identifying classes on the basis of growth trajectories of both quantity and frequency of alcohol use, we examined whether the latent trajectory classes predicted alcohol-related problems in Grade 12 and whether risk taking and emotional distress predicted the latent trajectory classes.

Our hypotheses are summarized in Figure 1. It should be noted that the hypothesized relationships in Figure 1 were tested in three separate analyses. The upper portion of Figure 1 shows latent growth curve models for quantity and frequency of alcohol use with covariances among the growth factors freely estimated. The arrows from the latent class variable to the growth factors indicate that the growth factors means vary across classes. That is, latent classes are identified by different patterns of change in both quantity and frequency of alcohol use. The arrows from risk taking and emotional distress represent a multinominal logistic regression predicting the latent classes. Finally, the arrow from the latent class variable to alcohol-related problems indicates that the probability of experiencing alcohol-related problems varies across classes. LGMMing in MPlus is estimated by maximum likelihood. This model assumes multivariate normal distribution of observed dependent variables conditional on predictors and class. Methods for assessing this assumption are not yet available.

Single-Domain Latent Growth Mixture Analysis

As a starting point, we determined the form of growth for both quantity and frequency of alcohol use using conventional polynomial growth models testing linear and quadratic growth, and we selected the model that best fit the data on the basis of model chi-square test, CFI, and RMSEA. Higher order polynomials (i.e., a random cubic effect) are not identified with four repeated measures. After identifying the best growth model for both quantity and frequency of alcohol use, we determined the number of latent classes on the basis of means of the growth factors. We started with the simplest assumption and hypothesized a single population. That is, we hypothesized one class and used latent growth factor mean values from this model as start values for a two-class model. Start values for the two-class model were determined by adding and subtracting 0.5 standard deviations from the latent growth factor means of the one-class model. In subsequent models, additional classes were included by adding and
subtracting 0.5 standard deviations from the latent growth factor means of the largest class.

We evaluated models in two ways. The Bayesian information criterion (BIC; Schwarz, 1978) was used to evaluate improvement in model fit when additional classes were added. Smaller BIC values suggest a better fitting model (B. Muthén & Shedden, 1999). Nagin (1999) demonstrated the usefulness of the BIC in identifying the optimal number of classes in finite mixture models. If the addition of a class resulted in a reduction in the model BIC relative to a previous model, then the new model was considered an improvement and the class was retained. One way to determine whether the reduction in the BIC is meaningful is to consider the probability that each model is correct. This probability is calculated using the BICs from each model (Kass & Wasserman, 1995, for details),\(^1\) and it is useful when comparing several mixture models to determine the number of mixtures (Nagin, 1999).

MPlus provides estimates of probabilities of membership in each class for each individual. For each individual these probabilities sum to 1.0. Ideally, for each individual, one of these probabilities would be very high (around 1.0) and the others very low (close to 0), indicating little ambiguity about class membership. Entropy is a summary measure of classification based on these probabilities (Ramasway, DeSarbo, Reibstein, & Robinson, 1993) that ranges from 0 to 1.0.\(^2\) The closer entropy values are to 1.0 the better the classification.

**Quantity of alcohol use.** We started with an intercept-only model and added a linear- and quadratic-growth factor to determine the form of growth for quantity of alcohol use. In each model the latent factor variances and covariances were freely estimated,

\[ p_j = \frac{e^{BIC_j - BIC_{\min}}}{\sum_i e^{BIC_i - BIC_{\min}}} \]

where \( p_j \) is the probability that Model \( j \) is the correct model, and \( BIC_{\min} \) is the minimum BIC score of the models under consideration.

\[ E_k = \frac{\sum_{i,k} (-\beta_{ik} \ln \hat{\beta}_{ik})}{n \ln K} \]

where \( \hat{\beta}_{ik} \) is the estimated probability for individual \( i \) in class \( k \).

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\(^1\) Entropy is calculated thus,

\(^2\) The closer entropy values are to 1.0 the better the classification.
and residual variances were freed to vary across time. The quadratic-growth model provided the best fit to the data, $\chi^2(1, N = 1,918) = 8.69, p = .09$ (CFI = .99, RMSEA = .02), and was used in subsequent LGMMing.

In our LGMMing, factor variances and covariances were estimated and residual variances were freed to vary across time, but these parameter estimates were constrained to be equal across classes because we wanted to identify classes on the basis of shared patterns of mean change rather than on variability. As shown in Table 1, the four-class solution was much more likely to be correct, and it produced the smallest BIC relative to the other models. This model was retained and suggested the following trajectories: (a) moderate escalation that slowed in later grades, (b) rapid escalation that slowed in later grades, (c) high initial quantity with de-escalation, and (d) moderate escalation that accelerated in later grades. None of the growth factor covariances were statistically significant (all $p s > .10$).

Frequency of alcohol use. Our analysis of frequency of alcohol use followed the same steps as our analysis of quantity. A simple linear-growth model provided a good fit to the data, $\chi^2(5, N = 1,918) = 8.69, p = .12$ (CFI = .98, RMSEA = .02). The addition of a quadratic-growth factor did not significantly improve fit, $\Delta \chi^2(4, N = 1,918) = 7.96, p = .09$. The linear-growth model with random intercept and linear factors was retained. LGMMing suggested that the three-class solution produced the lowest BIC and that it was much more likely to be correct than the one- or two-class solution (see Table 1). Entropy declined somewhat from the two- to the three-class solution; however, .96 for the three-class solution suggested excellent classification. The four-class model did not converge, suggesting that a fourth class could not be found. The three-class solution was retained and suggested the following trajectories: (a) high initial frequency with de-escalation, (b) moderate escalation, and (c) rapid escalation. It is notable that the de-escalating class was somewhat small ($n = 25$). The estimated variance for the linear-growth factor and the covariance between the intercept and linear-growth factor was not statistically significant ($p s > .10$), so these parameters were set to zero in subsequent models, which had little effect on model fit (BIC = 23,995.07, entropy = .95).  

Two-Domain Latent Growth Mixture Analysis

After establishing the number of trajectory classes for quantity and frequency, we modeled latent classes on the basis of both quantity and frequency growth trajectories. As a guide to determine the number of latent classes, class membership from the quantity and from the frequency LGMMing was output based on each case’s highest class probability, and a cross-tabulation was created, which was then used for estimating latent classes in our two-domain model. We started by estimating a one-class model on the basis of the largest cell in the cross-tabulation, using start values from our previous single-domain quantity and frequency LGMMing. Subsequent classes were added in descending order on the basis of cell-sizes in the cross-tabulation. The five-class solution provided the best fit to the data (see Table 1).

Results of the final two-domain LGMMing are presented in Table 2, and the trajectories are graphically presented in Figure 2. The first class was characterized by quantity and frequency that increased modestly, but never beyond infrequent very light drink-
Latent Trajectory Classes as Predictors of Alcohol-Related Problems in Grade 12

We next regressed alcohol-related problems in the latent trajectory classes. Only 18 adolescents experienced three or more alcohol-related negative consequences, so a three-category ordinal variable was created (no consequences, 1 consequence, 2+ consequences). Figure 3 shows probabilities of 0, 1, or 2+ consequences for each class. Zero problems was most common for all the classes except rapid escalators, who were more likely to experience 1 or 2+ rather than zero problems. All of the classes relative to the occasional very light drinkers showed elevated risk for alcohol-related problems. For example, 3% of occasional very light drinkers experienced 1 or 2+ consequences, but 35% of escalators did.

Risk Taking and Emotional Distress as Predictors of Latent Trajectory Classes

Finally, risk taking and emotional distress were included as predictors of the latent classes in multinomial logistic regression models with occasional very light drinkers as the reference group. Five percent of the sample (n = 104) were missing on the predictors and were consequently not included in these analyses.

Models with path coefficients from risk taking and emotional distress freely estimated and constrained to 0 were compared using a likelihood ratio test. The constrained model resulted in a significant decrement in model fit, $\chi^2(8, N = 1,814) = 35.79, p < .05$. Constraining the path coefficients from emotional distress and from risk taking to be equal across classes resulted in a decrement in model fit, $\chi^2(3, N = 1,814) = 56.20, p < .05$, and, $\chi^2(3, N = 1,814) = 14.84, p < .05$, respectively. Thus, risk taking and emotional distress predicted the latent classes, and their effects differed across classes. Results from the unconstrained model are presented in Table 3. An increase in risk taking increased the odds of being in all classes relative to the occasional very light drinking class, but this effect was somewhat weaker for escalators. The effects of emotional distress were weaker than those of risk taking. Emotional distress was not significantly associated with the odds of being an escalator or heavy drinker with declining frequency relative to an occasional very light drinker. Emotional distress increased the odds of being in the occasional heavy drinker and the rapid escalator classes.

Discussion

The current study identified trajectory classes on the basis of growth in both quantity and frequency of adolescent alcohol use and identified risk factors and consequences associated with the trajectory classes. LGMMing was used, which represents an ad-
Figure 2. Growth trajectories of quantity and frequency of alcohol use for each latent class.
vance beyond many other longitudinal grouping studies. The current findings suggest that the emergence of alcohol use during adolescence follows a variety of patterns. The dominant patterns included occasional very light drinker and escalator groups. On average, occasional very light drinkers consumed less than one drink per occasion in the past month throughout the study period. Escalators started at low levels of alcohol involvement in Grade 7 and progressed to consuming three–five drinks per occasion three times in the past month. Other adolescents (rapid escalators) were characterized by low quantity (one drink per occasion) and frequency (drinking less than once in the past month) in Grade 7 and rapid escalation to typically consuming three–five drinks 20 times in the past month. The final two classes showed elevated quantity of consumption throughout the study period, but one group drank infrequently (occasional heavy drinkers) and the other group showed a rapid decline in frequency (heavy drinkers with declining frequency).

Identifying longitudinal patterns of alcohol use is important because it can elucidate factors that contribute to divergent developmental trajectories. In this vein, we examined whether risk taking and emotional distress distinguished our drinking classes. High levels of risk taking increased the likelihood of being in all drinking groups relative to occasional very light drinkers, although this effect was strongest for the rapid escalator and heavy drinker classes. Other research has also shown that disinhibition (sensation seeking, risk taking, and impulsivity) is associated with adolescent alcohol use (e.g., Earlywine & Finn, 1991; Labouvie & McGee, 1986). Adolescents may view alcohol use as risky, exciting, and thrilling. After initiating drinking, positive affect associated with ingesting alcohol (e.g., euphoria) may lead to enhancement motivations to drink (drinking for fun or excitement) and subsequently to escalation of alcohol use and maintenance of heavy drinking. This appears to be particularly true for patterns of use characterized by rapid escalation or stable heavy drinking.

High levels of emotional distress were associated with increased likelihood of being an occasional heavy drinker or rapid escalator relative to an occasional very light drinker, and these findings are consistent with self-medication models of alcohol use (e.g., Russell & Mehrabian, 1975; Wills, 1990). Adolescents who experience high levels of emotional distress may be inclined to drink alcohol as a means of coping with their distress. It is unclear why emotional distress would be predictive of occasional heavy drinking and rapid escalation but not other longitudinal patterns. Perhaps negative reinforcement from alcohol (e.g., drinking to alleviate negative affect) accounts for rapid escalation. That is, after initiation, adolescents who are emotionally distressed may experience negative reinforcement, leading to rapid escalation in quantity and frequency of alcohol use. Occasional heavy drinking may represent episodic attempts to cope with emotional distress.

Table 3
Results From a Multinomial Logistic Regression (With Occasional Very Light Drinkers as the Referent)

<table>
<thead>
<tr>
<th>Drinking class</th>
<th>Regression coefficient</th>
<th>95% CI</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Escalators</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk taking</td>
<td>0.85</td>
<td>0.62–1.09</td>
<td>2.34</td>
</tr>
<tr>
<td>Emotional distress</td>
<td>0.12</td>
<td>−0.07–0.32</td>
<td>1.14</td>
</tr>
<tr>
<td>Occasional heavy drinkers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk taking</td>
<td>1.53</td>
<td>1.28–1.78</td>
<td>4.61</td>
</tr>
<tr>
<td>Emotional distress</td>
<td>0.53</td>
<td>0.29–0.77</td>
<td>1.70</td>
</tr>
<tr>
<td>Rapid escalators</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk taking</td>
<td>1.57</td>
<td>1.23–1.91</td>
<td>4.82</td>
</tr>
<tr>
<td>Emotional distress</td>
<td>0.39</td>
<td>0.09–0.69</td>
<td>1.47</td>
</tr>
<tr>
<td>Heavy drinkers with declining frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk taking</td>
<td>1.65</td>
<td>1.17–2.13</td>
<td>5.20</td>
</tr>
<tr>
<td>Emotional distress</td>
<td>0.33</td>
<td>−0.13–0.78</td>
<td>1.39</td>
</tr>
</tbody>
</table>

Note. CI = confidence interval; OR = odds ratio.
Our results suggest unique correlates of longitudinal patterns of alcohol use. Moderate escalation and a pattern of de-escalation are associated with risk taking, which is suggestive of a positive reinforcement mechanism of alcohol use (drinking to enhance). In contrast, risk taking and emotional distress were associated with occasional heavy drinking and rapid escalation. Both positive and negative reinforcement mechanisms may be operating to produce these longitudinal patterns. These mechanisms are speculative and require confirmation in future research. It should also be noted that the effects of risk taking were stronger than those of emotional distress, suggesting that risk taking may be more important for the early development of alcohol use.

Another important finding in the current study was that the identified patterns of alcohol use predicted alcohol-related problems in Grade 12. Specifically, a pattern characterized by rapid escalation of alcohol use was associated with the greatest risk for alcohol-related problems. B. Muthén and colleagues (B. Muthén & Muthén, 2000; B. Muthén & Shedden, 1999) similarly found that rapid escalation in heavy drinking in young adulthood increased the likelihood of alcohol dependence at age 30. The current article extends these findings by showing that rapid escalation in both quantity and frequency of alcohol use is a potentially destructive drinking pattern in adolescence.

It should also be noted that relative to occasional very light drinkers, all other patterns of drinking increased the likelihood of experiencing alcohol-related problems. This was true for escalators, a very large group that represented 36% of the sample. Thus, it appears that consumption beyond occasional very light drinking, which is common, increases risk for problems in Grade 12 and that rapid escalation is particularly problematic. This is not surprising given that alcohol use is an illicit behavior during this developmental period. Some caution is warranted when interpreting these findings, however, because the current measure of negative consequences included only five items, and inclusion of additional abuse and dependency symptoms in future research may yield a different pattern of findings.

Zucker, Fitzgerald, and Moses (1995) argued for the application of developmental psychopathology (see the special section “Clinical Adolescent Psychology: Developmental Psychopathology and Treatment” in the Journal of Consulting and Clinical Psychology; Holmbeck & Kendall, 2002) to adolescent substance use research because it promises to advance our understanding of etiological processes. A hallmark of developmental psychopathology is to examine longitudinal patterns of behavior at the individual level (person-centered approaches), and LGMMing is well suited to this goal (B. Muthén & Muthén, 2000). Specifically, LGMMing combines traditional latent growth models with latent class modeling, and this allows researchers to examine growth trajectories and classify individuals into homogenous groups on the basis of common patterns of change. A significant advancement of this approach beyond other longitudinal grouping strategies (e.g., cluster analysis) is that the classes are latent and take into account unreliability of classification.

As illustrated in this article, LGMMing offers an opportunity to identify patterns of change in adolescent alcohol use and to examine etiological processes that might predict a variety of growth trajectories in alcohol use and how longitudinal patterns may be linked to later outcomes. LGMMing is a generalization of structural equation modeling, and this allows much flexibility in how these models are estimated. We have made some a priori decisions on how to parameterize our models that may or may not be desirable in some applications. For example, we constrained error variances and latent growth factor variances and covariances to be equal across classes because we wanted to identify subpopulations on the basis of patterns of mean change rather than on within-class heterogeneity, and we wanted to examine individual differences and consequences that might distinguish the latent classes. Other questions of interest may dictate different choices. Error variances in growth models represent time-specific variability, and freely estimating them across classes would be important if a researcher expected time-specific variability to be greater in some classes than others. In this case, questions may focus on predicting time-specific variability, then error variances would be freed across classes, and time-specific predictors (e.g., availability of alcohol) could be included in the model with regression coefficients freed to vary across classes. Freely estimating latent variances and covariances would be important if there were interest in predicting growth factors within classes. For example, a researcher might hypothesize that parental drinking predicts growth factors and that this relationship varies across classes. In that case, growth factors could be regressed on parental drinking, and factor variances and path coefficients would be freed to vary across classes. In sum, the current strategy and modeling decisions made should be viewed in the context of the basic questions of interest, and it should be noted that LGMMing is a very flexible data-analytic tool that could be used to address a variety of questions.

Despite the strengths of the present work, there are also limitations of this study. First, a limited number of items were used to measure risk taking, emotional distress, and negative consequences. Also, the quantity of alcohol use was assessed using a limited range of response options. It would be important for future research to use more expanded assessment of these constructs.

Second, we focused on two risk factors to demonstrate the utility of LGMMing, and alcohol use is determined by a wide array of influences. Several other possible influences include familial and peer variables and other more proximal predictors (i.e., expectancies and perceived norms). It is important for future research to expand on what we have done by including a broader set of influences in future LGMMing of adolescent alcohol use. Finally, our assessments began in Grade 7, and by this time some adolescents had already initiated alcohol use. It will be important for future research to extend the ages of assessment so that onset can be examined, as well as the long term sequelae of alcohol use into young adulthood.

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