Identifying Trajectories of Adolescent Smoking:
An Application of Latent Growth Mixture Modeling

Craig R. Colder
State University of New York at Buffalo

Paras Mehta
University of Illinois at Chicago

Kevin Balanda
University of Queensland Medical School

Richard T. Campbell
University of Illinois at Chicago

Kathryn P. Mayhew
St. Cloud State University

Warren R. Stanton
University of Queensland Medical School

Mary Ann Pentz
University of Southern California

Brian R. Flay
University of Illinois at Chicago

The goal of the current study was to identify discrete longitudinal patterns of change in adolescent smoking using latent growth mixture modeling. Five distinct longitudinal patterns were identified. A group of early rapid escalators was characterized by early escalation (at age 13) that rapidly increased to heavy smoking. A pattern characterized by occasional puffing up until age 15, at which time smoking escalated to moderate levels was also identified (late moderate escalators). Another group included adolescents who, after age 15, began to escalate slowly in their smoking to light (0.5 cigarettes per month) levels (late slow escalators). Finally, a group of stable light smokers (those who smoked 1–2 cigarettes per month) and a group of stable puffers (those who smoked only a few puffs per month) were also identified. The stable puffer group was the largest group and represented 25% of smokers.

Key words: adolescent, smoking, trajectories, longitudinal

The health compromising effects of cigarette smoking are well known. Cigarette smoking is the leading cause of preventable death and disease in the United States (U.S. Surgeon General, 1989). It accounts for the majority of lung cancer cases, and it is an important risk factor for cardiovascular disease (U.S. Surgeon General, 1988). Although use of other substances, such as alcohol and marijuana, typically decline in young adulthood, cigarette smoking is fairly persistent during this period (Chen & Kandel, 1995). Moreover, intervention efforts have been met with limited long-term success in helping smokers stop smoking (e.g., Curry, Marlatt, Gordon, & Baer, 1988; Klesges et al., 1988). Prevention efforts have had little impact among adolescents who initiate smoking prior to the intervention (Ellickson, Bell, & McGuigan, 1993; Flay et al., 1989; Murray, Pirie, Luepker, & Pallonen, 1989; Vartiainen, Pallonen, McAlister, & Puusa, 1990). These findings suggest the importance of developing prevention programs that target smoking prior to initiation. For such prevention programs to be successful, it is necessary to better understand the timing of initiation and escalation of cigarette use.

Epidemiological data suggest that incidence rates of cigarette use rise during adolescence (Chen & Kandel, 1995; Kandel & Logan, 1984). Data from the Monitoring the Future Study indicate that by 12th grade, 37% of adolescents reported current smoking (within the last 30 days) and 24% reported daily smoking (Johnston, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998). Moreover, smoking rates (i.e., the number of cigarettes smoked per week) increase during adolescence, particularly during late adolescence (Bachman, Wadsworth, O'Malley, & Bachman, 1998).
for the initiation and escalation of cigarette use, little is known about the potential heterogeneity in how smoking behavior unfolds over time.

Identifying different patterns of smoking onset and escalation is important because such heterogeneity has implications for research and intervention. For example, specific trajectories of smoking may be linked to different etiological pathways. Thus, identifying homogeneous subgroups on the basis of common longitudinal patterns of cigarette use may provide researchers with a better understanding of the etiology of smoking behavior and may help identify high-risk groups. Similarly, identifying distinct longitudinal patterns may reveal different optimal ages for the implementation of smoking prevention programs across subgroups. For some youth who have no personal experience with cigarettes, early intervention may be ineffective (Maggs, Schultenberg, & Hurrelmann, 1997). Thus, identifying different patterns of onset and escalation may be important for the development and implementation of effective interventions. The goal of this article is to identify homogeneous subgroups of adolescents on the basis of smoking trajectories.

Currently, there are few studies that have examined trajectories of adolescent smoking. An exception is the work of Chassin, Presson, Rose, and Sherman (1996). Their outcome of interest was a dichotomous variable, the presence or absence of regular smoking (at least weekly), which was assessed over three time points. Results suggested that, on average, smoking increased from adolescence to young adulthood and stabilized after young adulthood. The dichotomous outcome and limited number of time points precluded examination of individual variability or heterogeneity in this trajectory. In another study that examined trajectories of smoking, Andrews and Duncan (1998) modeled growth in frequency of smoking from early adolescence (mean age = 13 years) to middle adolescence (mean age = 17 years). On average, frequency of smoking escalated with age, and there was significant variability in initial levels of smoking as well as rates of change. These findings suggest considerable heterogeneity in smoking trajectories.

In several articles, Chassin and colleagues (Chassin, Presson, Pitts, & Sherman, 2000; Chassin et al., 1996; Chassin, Presson, Sherman, & Edwards, 1990, 1992) used data collected from early adolescence to adulthood to examine a variety of longitudinal patterns of smoking. In contrast to Andrews and Duncan (1998), who modeled continuous heterogeneity in escalation of smoking by estimating variances of latent growth factors, Chassin and colleagues identified homogeneous subgroups on the basis of common longitudinal patterns of smoking. For example, Chassin et al. (1990) a priori categorized adolescents on the basis of 4 years of smoking data and examined whether the pattern and course of adolescent smoking predicted adult smoking. Rapid and slow onset of adolescent smoking did not differentially predict risk for regular (at least monthly) adult smoking. However, youth identified as stable smokers, on the basis of their report that they smoked at least monthly for 2 or more consecutive years, were more likely to be regular adult smokers than were adolescents who were erratic in their smoking.

Chassin et al. (2000) extended their work by empirically identifying distinct trajectories of smoking using data that extended from adolescence to adulthood. After removing lifetime abstainers and erratic smokers (those whose smoking decreased and then increased), four distinct trajectories were identified. Early onset stable smoking was characterized by escalation after age 11 and reaching maximum levels of smoking by age 15 (1–10 cigarettes). Late onset stable smoking was characterized by escalation after age 14 and leveling off at maximum levels by age 24. Experimental smokers were characterized by a relatively early age of onset, and their smoking never escalated beyond two cigarettes per week and declined after age 20. Finally, a quitter group was identified and included individuals who began smoking after age 14 with escalation to 11–20 cigarettes per day by age 20 and then a decline thereafter.

The work of Chassin and colleagues (Chassin et al., 1990, 1992, 1996, 2000), and the identification of smoking trajectories, represents a significant advancement in our understanding of patterns of youth cigarette use because it allows researchers to better tease apart the unique etiological processes that may be linked to specific longitudinal patterns of smoking. We expanded on Chassin et al.’s (1990, 1992, 1996, 2000) work by modeling rates of escalation (and perhaps deescalation) in smoking and heterogeneity of these patterns using latent growth mixture modeling. Latent growth mixture modeling is a general form of latent growth modeling, with the addition of an unobserved categorical variable. The unobserved categorical variable represents latent classes or mixtures.

Conventional latent growth modeling has become a common way of modeling individual differences in growth in an outcome, such as substance use (Andrews & Duncan, 1998; Duncan & Duncan, 1996; Willett & Sayer, 1994). 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 typical growth trajectory in the sample, and the variance around these means represents heterogeneity or individual differences in growth. Thus, heterogeneity in growth is captured by the variance estimates of latent growth factors.

Latent growth mixture models express heterogeneity differently. An alternative is to express heterogeneity in growth trajectories in a discrete, rather than a continuous, fashion. Here, the goal is to identify discrete classes or homogeneous subgroups of individuals on the basis of common patterns of growth. Latent growth mixture models model heterogeneity in growth by identifying discrete classes or mixtures (B. Muthén & Shedden, 1999). This is a new data-analytic strategy that has not been widely used in health

1 A latent growth mixture model models unobserved heterogeneity in growth where different individuals can belong to different subpopulations. The subpopulations are not observed but rather are inferred from the data and are represented as latent classes (or mixtures). Latent growth mixture models have two parts. The first part is the general model for continuous dependent variables (here, monthly smoking) that can be viewed as a traditional growth model. It is applied to all mixtures with some parameters allowed to vary across mixtures (e.g., latent growth factor means). The second part is a latent class model by which different subpopulations are represented. It is the second part of the model (the latent class part) that sets latent growth mixture modeling apart from traditional growth models. Traditional growth models do not identify latent subpopulations. Our latent growth mixture models were estimated in Mplus (L. K. Muthén & Muthén, 1998), which uses the expectation maximization algorithm and bootstrap standard errors. For more technical details of these models, see B. Muthén and Shedden (1999).


psychology literature. Thus, we provide extensive detail about the choices made and steps taken to estimate our models. Our models were estimated in Mplus software (L. K. Muthén & Muthén, 1998), currently the only software available for estimating latent growth mixture models.

On the basis of prior research by Chassin and colleagues (Chassin et al., 1990, 1992, 1996, 2000), we expected to find at least three distinct longitudinal smoking patterns in our adolescent sample—stable nonsmokers, early onset escalators, and late onset escalators. On the basis of findings that smoking may begin very early (prior to age 12; Kandel & Logan, 1984; Stanton et al., 1991), we also anticipated a possible fourth pattern, stable smokers. Chassin et al. (2000) identified quitters in their young adult data, but it remains unclear whether this pattern would emerge prior to young adulthood. Thus, it is possible that a quitter group would be apparent in our sample. In summary, we expected to find between three and five trajectories of adolescent smoking.

Method

Sample

Participants were selected from Project STAR, an intervention program designed to prevent adolescent substance use (Pentz et al., 1989). Only youth from the control group of the Kansas City metropolitan area sample were considered for inclusion in this study (N = 502). Data were collected during in-school surveys from two grade cohorts. The first assessment occurred in the fall of 1984, when the sample was in the sixth or seventh grade. The second assessment occurred in the spring of 1985. Subsequent assessments occurred annually in the spring for 4 more years. Thus, data were collected over six waves of assessment starting when the sample was in the sixth or seventh grade and ending when they were in the 10th or 11th grade. Current latent growth mixture modeling requires complete data, and therefore only cases with data from all six time points were included in the analysis (N = 323). This sample of 323 was approximately equally split by gender (N = 169 or 52% were female). At the first assessment, the age range was 11–13 years and the majority of the sample was 12 years old (68%). The majority of the adolescents were Caucasian (N = 254 or 79%), 57 (18%) were African American, 11 (3%) were Asian Pacific or Asian Indian, and 1 (0.3%) adolescent reported “other” for their ethnicity. Missing data occurred because of attrition or nonresponse (N = 179 cases). Analyses of variance (ANOVAs) and chi-square analyses were used to compare cases with missing data to those with complete data on Wave 1 measures. Comparisons on Wave 1 smoking and gender suggested no significant differences between cases with missing data and cases with complete data (both ps > .10). However, sixth graders were more likely to have missing data than seventh graders (p < .01).

Procedure

Surveys were administered in classrooms and consisted of 100 items pertaining to substance use, demographics, and psychosocial variables related to drug use. Details of the procedures are published elsewhere (see Pentz et al., 1989).

Measures

The number of cigarettes adolescents smoked in the past month was calculated using self-report data. Adolescents who reported lifetime smoking (even one puff of a cigarette) were asked to report the number of cigarettes they smoked in the past month and in the past week (0 = none to 5 = more than a pack). They were also asked to report how many cigarettes they smoke now (1 = I used to smoke, but now I don’t, 2 = I’ve only tried a few puffs, 3 = a few cigarettes a month or less, 4 = less than a pack a week, 5 = about a pack a week, 6 = about half a pack a day, 7 = a pack a day or more). Values on each item were recoded to the lower bound of each response category (e.g., more than a pack was converted to 21 cigarettes), and then responses were converted to a monthly rate. The maximum value across the three items was taken to represent monthly smoking. Skewness and kurtosis statistics suggested that the monthly smoking variables were nonnormally distributed, particularly in the earlier waves. One was added to these variables, and then they were transformed using the log transformation as suggested by Neter, Wasserman, and Kutner (1985) and B. Muthén (personal communication, October 28, 1999).

Results

Modeling Strategy

The goal of the current study was to identify classes of adolescents on the basis of the timing and rate of escalation of monthly cigarette use, and, therefore, adolescents who reported nonsmoking throughout the study period were excluded from our latent growth mixture models (n = 63). Inspection of the sample means across time suggested that change in smoking followed a complex pattern. Smoking escalated slowly over the first three assessments, rapidly between the fourth and fifth assessments, and slowly again between the last two assessments.

Because we wanted to model different times and rates of escalation across subgroups of smokers, we fitted several forms of growth trajectories to the data, including linear, quadratic, and piecewise growth (a two-piece model). Piecwise growth models describe discontinuity in growth. For example, they allow for potentially nonlinear growth processes in which the rate of change in the outcome accelerates rapidly at a given time. Polynomial growth models are not useful for describing a rapid shift in the rate of change. Our piecewise models reflected two-piece growth in which the rate of change in cigarette use shifted at a given age (discontinuity in the rate of change). The piecewise growth model provided the best fit to the data and the best description of the classes.

In their review, Eccles, Lord, Roeser, Barber, and Hernandez Jozefowicz (1997) concluded that a variety of socioemotional and behavioral variables show discontinuous change during adoles-

---

2 Raw-maximum likelihood (e.g., Arbuckle, 1996) and multiple imputation (e.g., Schafer, 1997) are two approaches to missing data that can be implemented in conventional latent growth curve models. Both of these approaches make a strong assumption that there is a single population. Growth mixture modeling, in contrast, represents a model that challenges the notion of a single population. In fact, growth mixture modeling hypothesizes multiple latent populations. As a result, conventional missing-data methods available for a single group latent growth curve are not appropriate for the growth mixture modeling case. Missing-data methods suitable for mixture modeling are still in early stages of development (B. Muthén, personal communication, June 9, 2000). As a result, we were restricted to using cases with complete data.

3 Modeling piecewise growth is not a requirement of latent growth mixture modeling. We chose to use piecewise growth models because they showed the best fit to the data and because such models offered maximum flexibility in specifying different ages of inflection for the growth trajectories across the latent classes.
ence. Similarly, Sayer and Willett (1998) found that adolescents’ positive expectancies about the effects of alcohol followed a piecewise growth pattern, such that positive expectancies increased slowly from Grade 5 to Grade 6 and escalated more rapidly after Grade 7. Accordingly, one might expect adolescent substance use to increase gradually in early adolescence and then escalate rapidly thereafter. Our piecewise growth model allowed for examination of such a discontinuous growth process. In summary, the final latent growth mixture models were based on piecewise growth because this pattern offered the best fit to the data and allowed us to model a rich set of growth patterns (i.e., different times of escalation and rates of change). We started with one class and added additional classes on the basis of different starting points and rates of escalation.

Residual variances were estimated to be a function of the mean levels of smoking both within and across classes. That is, we expected low mean levels of smoking to be associated with relatively low error variances, and as mean levels of smoking increased, residual variances were expected to increase as well. For example, for the stable very light smoking class, residual variances were constrained to be equal over time, and a relatively small start value was specified for these parameters to reflect small error variances associated with the low mean levels of smoking. Residual variances for repeated measures of smoking were also constrained to be equal across classes when mean levels of smoking were similar at a particular time. For example, if at Time 1, mean smoking was similar across two classes, then the residual variance corresponding to Time 1 smoking was constrained to be equal across these two classes.

The above described constraints placed on parameters were important for model identification. Identification of growth mixture models is an empirical issue and cannot be determined algebraically. The identification of a growth mixture model depends on sample size and the number of variables, classes, and parameters estimated. The constraints placed on residual variances helped achieve identification of our models. We also started with the simple hypothesis that the initial rate of escalation, regardless of when the escalation began, would be the same across classes. This constraint also helped achieve identification and was relaxed where possible.

We evaluated our models in several ways. We used the Bayesian Information Criterion (BIC; Schwarz, 1978) to evaluate improvement in model fit when additional classes were added or parameters were constrained. 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 an adjustment to one of the current models, such as a constraint or an added class, resulted in a reduction in the model BIC relative to a previous model, then the adjustment was considered an improvement to the model and was retained.

Our latent growth mixture models were estimated in Mplus Version 1.03 (L. K. Muthén & Muthén, 1998), which provides estimates of probabilities of class membership for each individual. For example, in a five-class solution, five probabilities are estimated for each individual in the data, where each estimates the likelihood that an individual is a member of one of the classes. 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. We also used these probabilities to evaluate our models. For individuals who were poorly classified, that is, those who had several moderate probabilities, we looked at their raw data to decide if the addition of another class was necessary and substantively meaningful. In summary, both the model BIC and estimated probabilities were used to evaluate and adjust our solutions at each step of the modeling process. Moreover, our theoretical expectations about adolescent smoking also guided our identification of classes.

**Final Latent Growth Mixture Models**

We used a two-piece growth model to describe change in the level of smoking in log scale over the entire study period for all classes. For a given latent class, an increase in the level of smoking in log scale can be described by two line segments, each representing different rates of change. The parameters of such a two-piece growth model are (a) the level of smoking (log of cigarettes per month) at the first assessment, (b) the rate of change during the first change segment, (c) the age inflection or the age at which a shift in the rate of change occurs, and (d) the rate of change during the second change segment. The age of inflection, therefore, demarcates change in the rate of increase for log smoking. We presented our findings both in terms of the model parameters in log scale, as well as in terms of the original metric (i.e., number of cigarettes smoked per month). Because log transformation is a nonlinear transformation, our use of piecewise growth modeling allowed us to model a rich set of nonlinear growth trajectories within the context of linear growth modeling. It should be noted that statistical inferences about parameters in the model (e.g., growth factor means) are based on log-transformed variables. The trajectories based on the original metric are presented for descriptive purposes.

Five latent classes were identified. Table 1 presents the parameters of the growth mixture modeling in log scale. For the first group, growth was modeled as a single piece, with age of inflection occurring before the first occasion of measurement. For the second and third classes, inflection in the rate of change in log smoking occurred at ages 13 and 15, respectively. The last two classes were composed of stable smokers, and their smoking remained constant throughout adolescence. To aid substantive interpretation, we provide Table 2, which presents the expected level of smoking in terms of number of cigarettes smoked per month at each assessment (in both original and log-transformed metric) and predicted frequencies (f) for each class. Figure 1 presents the same information graphically. As expected, conversion of monthly smoking from log scale to original scale resulted in noticeably nonlinear trajectories, especially for the escalating classes.

In early adolescence (between ages 12 and 13), the average level of monthly smoking was light across all classes (< four cigarettes per month). One class, early rapid escalators, exhibited early escalation (between ages 12 and 13), and their smoking increased rapidly after age 13, such that by age 16, adolescents in this class typically smoked 156.81 cigarettes per month. Another class, late moderate escalators, smoked very lightly (on average only a few puffs per month) until age 14, at which point they exhibited moderate escalation. By age 16, these late moderate escalators
Table 1

Growth Factor Means (in Log-Transformed Metric) for Each Smoking Group

<table>
<thead>
<tr>
<th>Smoking group</th>
<th>Intercept</th>
<th>1st piece</th>
<th>2nd piece</th>
<th>Age of inflectiona</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early rapid escalators</td>
<td>.50*</td>
<td>1.18*</td>
<td>1.18*</td>
<td>&lt;12</td>
</tr>
<tr>
<td>Late moderate escalators</td>
<td>.02*</td>
<td>0.01*</td>
<td>1.18*</td>
<td>13</td>
</tr>
<tr>
<td>Late slow escalators</td>
<td>.03*</td>
<td>0.01*</td>
<td>0.90*</td>
<td>15</td>
</tr>
<tr>
<td>Stable light smokers</td>
<td>.92*</td>
<td>-0.01</td>
<td>-0.01</td>
<td>NA</td>
</tr>
<tr>
<td>Stable puffers</td>
<td>.05*</td>
<td>0.00</td>
<td>0.00</td>
<td>NA</td>
</tr>
</tbody>
</table>

a For those classes with relatively flat rates of change there is no age of inflection and hence it is indicated with NA (not applicable).

*p < .05.

typically smoked 34.54 cigarettes per month. The remaining three classes were characterized by light smoking throughout the study period. Late slow escalators smoked only a few puffs per month until age 15, when they escalated to 5.31 cigarettes per month. A class of stable light smokers was also identified. On average, this group smoked between one and two cigarettes per month throughout the study period. Finally, a stable puffer class was identified. This group typically smoked only a few puffs per month throughout the study period. As shown in Table 2, the predicted frequencies (p) suggest that among adolescent smokers, the stable puffer group was the largest and the early rapid escalators group was the smallest. This indicates that early rapid escalation was a relatively atypical trajectory in this sample of adolescent smokers.

One feature of latent growth mixture modeling is that predicted probabilities for each class are estimated for each individual in the data. These probabilities represent the certainty with which a particular individual can be classified into each class. Ideally, an individual will have a high predicted probability for one class and low probabilities for the remaining classes. This would suggest little ambiguity of class membership. To examine this aspect of the model, predicted probabilities of class membership were plotted to evaluate our five-class solution. Specifically, an observed (vs. latent) mixture variable was created by classifying individuals into one class on the basis of their highest predicted probability. Cumulative frequency distributions were then constructed for each class, as presented in Figure 2. The predicted probabilities were typically very high for each class (see Figure 2). For example, the first distribution shows the cumulative frequency distribution of predicted probabilities of being an early rapid escalator among those adolescents who were actually classified as early rapid escalators. The predicted probabilities for early rapid escalators ranged from .51 to 1.0 and were >.90 for the majority (86%) of the adolescents actually classified as early rapid escalators. A similar pattern emerged for each class. These findings suggest that there was little ambiguity in categorizing adolescents into the five smoking classes and that the classes were well differentiated.

Discussion

The aim of this article was to empirically identify trajectories of adolescent smoking using a newly emerging data-analytic strategy—latent growth mixture modeling. Discrete patterns of smoking were identified on the basis of level of smoking, the point at which smoking began to escalate, and the rate of escalation. Analyses revealed considerable heterogeneity in how smoking unfolded over time during adolescence. Prior to age 13, the typical level of smoking was very light and could be characterized as trying cigarettes (or trial behavior). After age 13, patterns of smoking began to diverge, with some youth remaining at very low levels of use and others escalating more or less rapidly to higher levels of use.

Five distinct patterns of cigarette smoking were identified—early rapid escalators, late moderate escalators, late slow escalators, stable light smokers, and stable puffers. After age 13, some adolescents went on to experiment more regularly and then rapidly escalated in their smoking after age 15 to fairly high levels (> 150 cigarettes per month). We labeled this pattern of smoking early rapid escalation. Chassin et al. (2000) also identified a trajectory

Table 2

Average Number of Cigarettes Smoked per Month at Each Wave of Assessment

<table>
<thead>
<tr>
<th>Smoking group</th>
<th>12</th>
<th>12.25</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early rapid escalators</td>
<td>0.05</td>
<td>0.41</td>
<td>3.59</td>
<td>13.92</td>
<td>16.81</td>
<td>50.96</td>
<td>28.34</td>
</tr>
<tr>
<td>Late moderate escalators</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>2.36</td>
<td>9.93</td>
<td>11.09</td>
<td>45.33</td>
</tr>
<tr>
<td>Late slow escalators</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>1.58</td>
<td>1.84</td>
<td>54.72</td>
</tr>
<tr>
<td>Stable light smokers</td>
<td>1.50</td>
<td>1.50</td>
<td>1.48</td>
<td>1.46</td>
<td>1.44</td>
<td>1.43</td>
<td>49.61</td>
</tr>
<tr>
<td>Stable puffers</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>81.90</td>
</tr>
</tbody>
</table>

a Ages are mean ages. Numbers in parentheses are means in log-transformed metric.

b f represents predicted frequencies for each smoking group.
characterized by early escalation (prior to age 12). These data suggest that for some adolescents it would be important to intervene in early adolescence before trial behavior escalates to experimentation and then heavy smoking.

Other groups included adolescents who, after age 15, began to escalate slowly in their smoking to light (5.31 cigarettes per month) or moderate (34.54 cigarettes per month) levels. We labeled these groups late slow escalators and late moderate escalators, respectively. Of interest is whether these late escalating groups will continue to smoke at light and moderate levels, will exhibit a pattern of rapid escalation as they enter adulthood, or will quit. It is possible that these groups never escalate to heavy levels of smoking and in adulthood become what has been referred to as "tobacco chippers" or occasional smokers who smoke at low rates (Hennrikus, Jeffery, & Lando, 1996; Owen, Kent, Wakefield, & Roberts, 1995; Shiffman, 1989).

Another possibility is that the slow escalating groups who smoke at low or moderate levels may represent late starters who will follow a pattern, albeit delayed, similar to the early rapid escalators. Indeed, Chassin et al. (2000) identified a group of late escalating smokers who reached high levels of smoking by early adulthood (1–10 cigarettes per day by age 20) and never showed a decline. Thus, it is possible that some of the late escalators in our sample smoked at heavy levels later in adulthood. Some researchers have advocated for delaying the onset of cigarette smoking as a goal for prevention programs (e.g., Everett, Warren, Sharp, Kann, Husten, & Crossett, 1999). However, given that late escalators represented a substantial number of smokers and that some adolescents from this group may go on to smoke at elevated levels, delaying the age of onset and of escalation of smoking may not be a prudent goal.

Finally, a group of stable light smokers was identified. This group may be composed of adolescents who occasionally have part of a cigarette. Perhaps these adolescents smoke for social reasons, such as when they are at a party.

Our findings have important implications for future research and intervention. First, we found that there is considerable variability in the sequelae of cigarette use among adolescents who try cigarettes—some adolescents escalate to heavy smoking, some remain very light users, and others escalate to moderate levels of smoking. Findings that point to diverse patterns of smoking initiation and escalation suggest the need to better understand these processes. For example, identifying the characteristics of light smokers who do not escalate might reveal important variables that buffer adolescents from the uptake process to heavy smoking. Similarly, identifying the characteristics of escalators might indicate important variables that potentiate the uptake process to heavy smoking. Early rapid escalators may have a biological or genetic liability for
addiction to nicotine and this might suggest the need for pharmaco-logical intervention with this group, whereas stable light smok-ers may represent social smokers who do not possess such a biological liability. Identifying the unique causal processes associated with different patterns of cigarette use is an important direction for future research, which may eventually shape the content of future interventions. Moreover, identifying risk factors that are specific to escalation may help identify subgroups of adolescents that would be important targets for intervention. It may not be necessary to use limited resources to intervene with light stable smokers.

Second, our findings suggest considerable variability around the timing of escalation of cigarette use. Future research is warranted to examine the processes that might account for the onset of escalation in smoking at different developmental periods (e.g., peer pressure, life stress). Such research would provide important information about the processes involved in the early stages of the smoking uptake process.

Finally, there are a variety of ways to analyze growth processes. One approach that is increasingly implemented with repeated measures of adolescent substance use is latent growth modeling. In this article, we demonstrated the use of latent growth mixture modeling, which extends latent growth modeling in an important way. Unlike traditional growth models, latent growth mixture models identify subpopulations on the basis of distinct growth trajectories. This approach may have more explanatory utility than traditional growth models when theory suggests a variety of different forms of growth (e.g., different ages of onset and escalation and growth curves of different shape) that are qualitatively distinct. For example, one might speculate that adolescents who initiate and rapidly escalate in smoking early (prior to age 12) compared with those who initiate and escalate later (after age 17) represent distinct subgroups whose smoking may be linked to different etiological processes (e.g., early problem behavior vs. unconventionality).

Currently, growth mixture modeling can be implemented in two programs that are accessible and relatively easy to use, Mplus (L. K. Muthén & Muthén, 1998) and Proc Traj in SAS (Jones, Nagin, & Roeder, 1998). Each computer program has merit. For example, Mplus specifies latent growth mixture models in the context of a general structural equation model. This allows considerable flexibility in model specification (e.g., specifying latent variables, estimating a variety of residual variance structures). However, Mplus (version 1.04) does not permit the inclusion of cases with missing data and assumes multivariate normality of the observed variables. In contrast, Proc Traj in SAS allows for the
inclusion of cases with missing data and specification of a variety of distributions for the observed variables but does not permit specification of latent variables. Health researchers interested in developmental processes should consider growth mixture models to analyze repeated measures data and to evaluate models of health behavior now that this data-analytic strategy is accessible.

In closing, limitations of the current study should be noted. First, our data-analytic strategy required complete data, which resulted in some participant loss. It has been argued that participants who drop out of studies, particularly school-based studies, are at greater risk for substance use (Chassin, 1984), which has been supported by epidemiological research (Beauvais, Chavez, Getting, & Defenbacher, 1996). Thus, the current findings should be generalized with caution. Second, we did not examine potential predictors of smoking trajectory classes. An important next step is to include predictors that may distinguish different classes of adolescent smokers. Despite these limitations, the current study demonstrated the utility of a newly emerging data-analytic strategy for examining growth processes that will be useful to health researchers. The current findings suggest that trajectories of adolescent smoking are quite heterogeneous and that latent growth mixture modeling is a useful and descriptively rich strategy for modeling such heterogeneity.

References