EVALUATION OF LONGITUDINAL INTERVENTION EFFECTS: AN EXAMPLE OF LATENT GROWTH MIXTURE MODELS FOR ORDINAL DRUG-USE OUTCOMES

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Heterogeneity often exists among behavioral growth trajectories in a study population. In the evaluation of intervention effects for longitudinal randomized trials, it is informative to examine the impact of an intervention on subgroups characterized by different types of growth trajectories. This paper presents an application of growth mixture modeling to an ordinal-scale substance-use behavior outcome from the Aban Aya Youth Project (AAYP), a longitudinal preventive intervention trial targeting health-compromising behaviors among adolescents. Results suggested two classes of adolescent substance use growth trajectories: Class 1 (44.7% of the sample) started at a higher level and had a relatively shallow increase over time; Class 2 had a lower baseline level and a rapid increase over time. The intervention effectively reduced the rapid increase of substance use for the adolescents in the second class.

INTRODUCTION

In prevention science, researchers increasingly rely on longitudinal designs to examine intervention effects on the development of behaviors. Major branches of methodology for the analysis of individual-level developmental trajectories include latent growth models (McArdle & Epstein, 1987; Muthén, 1989, 1991)

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and mixed-effects regression models for continuous (Bryk & Raudenbush, 1992; Laird & Ware, 1982) or categorical outcomes (Harville & Mee, 1984; Hedeker & Gibbons, 1994). These models for developmental trajectories assume that all individual trajectories are from a single population of growth curves with common population parameters, and the heterogeneity among individuals is captured by random effects on developmental parameters (e.g., random intercept and slope) from that single population of growth curves. However, the assumption of a single population of growth curves is often violated in the study of problem behaviors, as subgroups of growth profiles often exist. Ignoring the possibility that individuals come from different subpopulations may yield biased estimates of the random-effects parameters (Verbeke & Lesaffre, 1996), as well as failures in detection of intervention effects or other important predictive relationships within any one of the subpopulations (Muthén, 1989). In the past decade, methodology research has evolved, focusing on relaxing the assumption of a single population of growth curves to allow for a mixture of distributions. In the latent growth modeling framework, such development includes the growth mixture modeling (GMM) for continuous (Muthén, 2001, 2002; Muthén & Shedden, 1999) and categorical variables (Muthén, 2004), and a latent class growth analysis (LCGA) approach for continuous (Nagin, 1999), dichotomous (Nagin & Land, 1993), and count outcomes (Nagin & Tremblay, 2001). Similar methodology development can also be found in the mixed-effects regression framework (e.g., Verbeke & Lesaffre, 1996; Xu & Hedeker, 2001).

In studies of substance use behavior, it is important to identify different patterns of longitudinal growth trajectories because such heterogeneity may be linked to different etiological pathways and have implications for research and interventions. There are a growing number of studies examining patterns in substance use over time. For example, Flaherty (2002) applied the latent class model to data on adolescent cigarette smoking and identified five classes: experimenters, regular smokers, past experimenters, past smokers, and irregular smokers. Colder et al. (2001) employed GMM to examine the longitudinal patterns of change in smoking behavior of the control group of adolescents from Project STAR and identified five growth patterns: rapid escalators, occasional puffing-ups, slow escalators, stable light smokers, and stable puffers. Colder, Campbell, Ruel, Richardson, and Flay (2002) studied the alcohol use growth trajectories of the control adolescent sample of the Television, School, and Family Smoking Prevention and Cessation Project to examine alcohol use behavior. They simultaneously modeled the growth trajectories of both quantity and frequency of alcohol consumption to identify latent classes and examined the effects of covariates such as emotional distress and risk taking. The results indicated five longitudinal drinking patterns: occasional light drinking, moderate escalators, infrequent but high-level drinking, rapid escalators, and one group with high baseline frequency and quantity but rapid de-escalation in later frequencies of drinking.

With the use of a control group of individuals, these studies, as most of the studies that employ growth mixture modeling, focused on identifying latent classes of growth patterns in adolescent substance use behaviors; however, an examination of how interventions might have differential effects on the (different) subgroups of adolescents was not considered. In fact, in the literature of longitudinal intervention evaluations, the conventional single-population random coefficient growth modeling was still the predominant choice of analysis method. In investigations of violence interventions for adolescents, Segawa, Ngwe, Li, Flay, and Aban Aya Coinvestigators (2005) identified three distinct patterns of violence growth: persistent low-risk individuals, medium-risk individuals with moderate escalations, and high-risk individuals with rapid escalations. Their analysis of intervention effects revealed that the interventions were effective for high-risk individuals, i.e., students already engaged in extreme violent behaviors at baseline, but not so much for low- and medium-risk students. In addition, the effect size found in the high-risk class was three times larger than what was revealed using a conventional single-population analysis approach. More recently, Witkiewitz, van der Maas, Hufford, and Marlatt (2007) used Project MATCH data to examine the effect of treatment on three classes of drinkers (frequent, inconsistent, and infrequent drinkers), with self-efficacy as dynamic predictor. The use of GMM provided evidence in support of the relationship between treatment, self-efficacy, and the drinking outcomes, a relationship not revealed using the conventional analysis method.

The Aban Aya Youth Project (AAYP) was a longitudinal efficacy trial designed to compare the effects of two interventions on reducing health-compromising behaviors among African American students in disadvantaged areas in Chicago. Previous analysis using the conventional single-population growth models revealed that the two interventions, a Social Development Curriculum (SDC) and a School-Community Program (SC), compared with a control condition, the Health Enhancement Curriculum (HEC), were effective in reducing the growth of substance use among male African American students from grades five to eight (Flay et al., 2004). A GMM approach applied to violent behavior among AAYP students identified differential intervention effects among three classes of growth patterns (Segawa et al., 2005).

Our aim in this article is to employ the categorical latent growth mixture model described in Muthén (2004) to substance use behavior in the AAYP sample to (a) identify subgroups of male adolescent substance use growth trajectories; and (b) to reveal differential intervention effects among these subgroups of individuals. Mplus Version 4.1 (Muthén & Muthén, 1998-2003) was used to implement the analyses in this article. Mplus is a statistical package that allows the modeling of growth in the latent variable modeling framework via mean- and covariance-structure structural equation modeling (SEM). An overview of this type of modeling is given in Muthén (2004). Technical aspects of the modeling, estimation, and testing are given in Technical Appendix 8 of the Mplus User's Guide (Muthén & Muthén, 1998-2003) and Muthén and Shedden (1999).

We will first describe the model and some technical issues. The data used in this study are from the Aban Aya Youth Project (AAYP). An introduction to the project, including the programs, sample, design, etc., will be presented in the Aban Aya Youth Project section below. In the results section, we will present the results from a conventional growth model and the GMM model. We end the article with conclusions and discussion of difficulties one might encounter in implementing this kind of model.

MODEL DESCRIPTION

CONVENTIONAL GROWTH MODEL FOR CATEGORICAL OUTCOME

Let Y_{ij} denote the observed ordinal outcome for subject i (i = 1, 2, … , N) at time point j (j = 1, 2, … , n_i). Let the M ordered response categories be coded as m = 1, 2, … , M. Mplus uses the cumulative proportional odds logistic regression model (see, e.g., Agresti, 1990, pp. 321-324) for the probability of response. Define the cumulative probabilities for the M categories of the observed outcome Y_{ij} a

$$P_{ijm} = P(Y_{ij} \le m) = \sum_{l=1}^{m} p_{ijl} .$$

The conventional two-level linear growth model with a group indicator G_i (G_i = 1 for intervention, 0 for control) is given in terms of the cumulative logits as

Level 1 (Within subject): $$\log\left(\frac{P_{ijm}}{1-P_{ijm}}\right) = \alpha_m - (b_{0i} + b_{1i} T_{ij}) \qquad (1)$$

Level 2 (Between subject): $$\begin{aligned} b_{0i} &= \beta_0 + \beta_1 G_i + \upsilon_{0i} \\ b_{1i} &= \beta_2 + \beta_3 G_i + \upsilon_{1i} , \end{aligned} \qquad (2)$$

where b_{0i} and b_{1i} are random intercepts and slopes varying across subjects. The random intercept and linear trend effects υ_{0i}, υ_{1i} are assumed to be jointly normally distributed with zero means, variances σ^2_I and σ^2_S, and covariance σ_{IS}. Notice that the model above does not have a residual e_{ij}, because the residual variance is fixed in line with ordinary logistic regression. This model may be thought of as a threshold model for a latent continuous response variable so that the observed response Y_{ij} is determined by M-1 ordered thresholds, α_m ($m = 1, 2, \ldots, M$-1), with α_1 being fixed at zero commonly for identifiability. In this study, the logit growth of the substance use outcome follows a linear trend with subject variation in intercept and slope, and the only covariate used is the intervention indicator. Therefore, β_0 and β_2 are the mean intercept and slope for the control group, respectively, and β_1, β_3 are intervention differences in mean intercept and slope. More general forms for the model given in (1) and (2) may include any higher-order growth trend (fixed or random), as well as time-varying covariates (Hedeker & Gibbons, 1994).

The growth model above is presented as a two-level, mixed-effects model. Alternatively, the growth model can be seen as a latent variable model, where the random effects b_{0i} and b_{1i} are latent growth factors whose modeling is obtained via mean- and covariance-structure in the structural equation modeling (SEM) framework. Connections between multilevel, latent variable, and SEM growth analysis, as well as the advantages of placing the growth model in an SEM context are reviewed in Muthén (2004).

Growth Mixture Model Extension

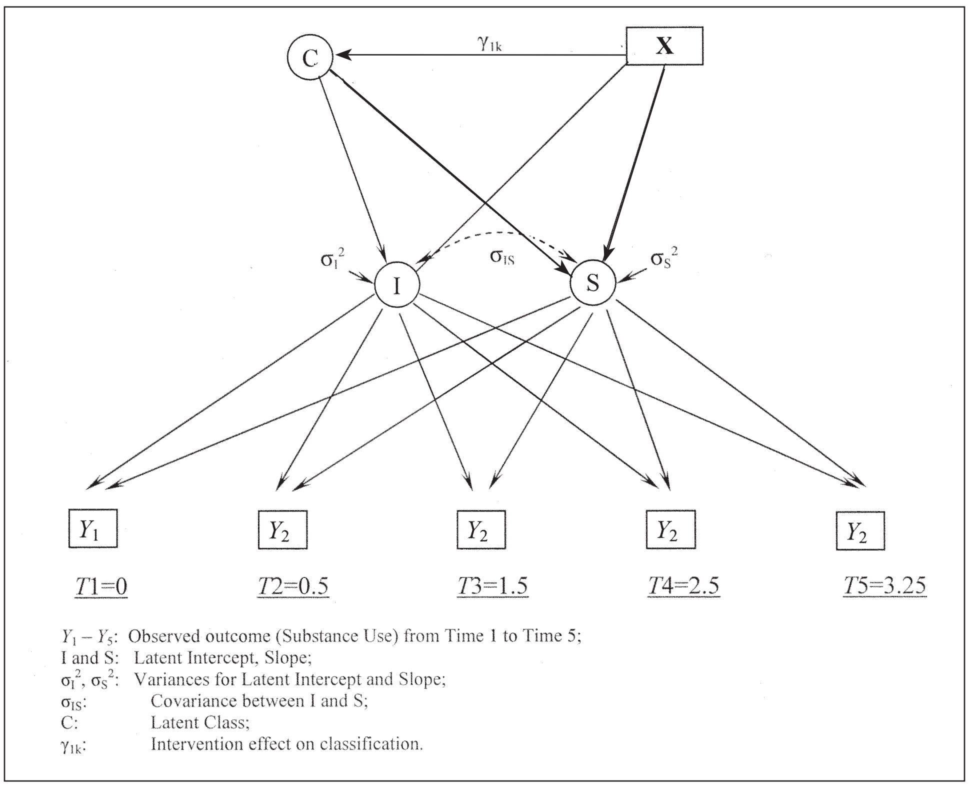
The model in (1) and (2) allows group differences as well as individual differences in development over time. The individual heterogeneity is captured by the random growth factors υ_{0i} and υ_{1i}. On the other hand, this model assumes that all individuals are drawn from a single population with common population parameters. Growth mixture modeling (GMM) allows one to relax the single population assumption through the use of latent trajectory classes, a categorical latent variable. Let c_i denote a latent categorical variable representing the unobserved subpopulation membership of subject i, $c_i = 1, 2, \ldots, K$. Alternatively, let C_{ik} ($k = 1, 2, \ldots, K$) be a set of indicators such that $C_{ik} = 1$ if subject i belongs to class k, $k = 1, 2, \ldots, K$, and zero otherwise. GMM extends the model in (1) and (2) by considering a separate growth model for each of the K latent classes. That is:

Level 1 (Within subject):
$$\log\left(\frac{P_{ijm}}{1-P_{ijm}}\right) = \alpha_m - (b_{0ik} + b_{1ik} T_{ij}) \quad (3)$$

Level 2 (Between subject):
$$\begin{aligned} b_{0ik} &= (\beta_{0k} + \beta_{1k} G_i + \upsilon_{0ik}) C_{ik} \\ b_{1ik} &= (\beta_{2k} + \beta_{3k} G_i + \upsilon_{1ik}) C_{ik}, \end{aligned} \quad (4)$$

for $k = 1, 2, \ldots, K$. Here, both the mean- and covariance-structure can be class-specific, while the thresholds are usually held constant across classes to ensure measurement invariance. In Mplus, such a logistic regression model for the probability of response typically assumes proportionality of the covariate effects. One can extend the above model in (3) and (4) so that the growth curves for different classes assume different mean shapes, including the possibility of higher-order polynomials, and/or different random-effect variance-covariance structures. For example, the growth curve for one of the latent class trajectories might be quadratic with random quadratic variation, while other classes assume linear growth with variance-covariance structure only involving random intercept and linear terms. In addition, other covariates, at the group-, individual-, or time-point level, can be added. Compared with the above GMM specification, a conventional latent growth model as in (1) and (2) is essentially a one-class growth mixture model.

Figure 1. Latent Growth Mixture Model Diagram



TESTING COVARIATE EFFECTS ON CLASSIFICATION

In Mplus, the growth mixture model stochastically classifies subjects to a pre-specified number of unobserved classes according to growth trajectories and covariate effects. An example of the model specification for a GMM with covariate X is shown in Figure 1. Notice that the covariate X influences the growth factors b_{0i} and b_{1i}, as well as the latent class c.

The classification of subject i, ($c_i = k$), given covariate x_i, is provided using a multinomial logistic regression model for the K classes:

$$P(c_i = k|x_i) = \frac{\exp(\gamma_{0k} + \gamma_{1k} x_i)}{\sum_{l=1}^{K} \exp(\gamma_{0l} + \gamma_{1l} x_i)} \ , \tag{5}$$

with the last class commonly being the reference class, i.e., $\gamma_{0K} = 0$ and $\gamma_{1K} = 0$. In the above logistic regression formulation, γ_{0k} is the logit intercept, i.e., log odds of being in class k versus the last class at $x_i = 0$, and γ_{1k} is the effect of one unit increase in the covariate on classification, i.e., the increase in the log odds of being in class k versus the last class for a unit increase in X. When X is dichotomous group indicator and coded 0, 1, γ_{1k} represents the group effect on classification. The formal test of γ_{1k} is informative and important for demographic covariates such as gender and ethnicity group, as it reveals whether and how the subgroup classifications differ between groups. When X is the intervention indicator, however, it is important that classifications are not affected by intervention/control condition, i.e., $\gamma_{1k} = 0$, so that any class-specific intervention effects found later would be attributable to the program, and not differences in membership classification. A test of this parameter determines whether the class-specific intervention effects are valid.

THE ABAN AYA YOUTH PROJECT

The ordinal outcome variable that we used in illustration of the model described above was substance use behavior from AAYP, a multi-year efficacy trial designed to compare the effects of two interventions on reducing health-compromising behaviors among African American students in disadvantaged areas in Chicago. The two interventions, namely, Social Development Curriculum (SDC), and School-Community Program (SC), were compared with a control condition, the Health Enhancement Curriculum (HEC). All interventions were implemented in grades 5 through 8 in 12 poor, predominantly African American, metropolitan schools in Chicago and its surrounding suburbs. A randomized-block design was used to assign schools to the three conditions after stratification on multiple indicators of risk. In the three conditions, the HEC program focused on promoting healthy behaviors and served as an active control condition for the other programs. The SDC program was a classroom-based social development curriculum designed to teach students cognitive-behavioral skills to build self-esteem and empathy, manage stress and anxiety, develop interpersonal relationships, resist peer pressure, develop decision-making and problem-solving skills; and teach goal-setting for the purpose of preventing drug use, violence, and unsafe sexual behaviors. The more comprehensive intervention, the SC condition utilized the SDC curriculum and also provided critical community empowerment components such as a parent support program, school staff and school-wide youth support programs, and a community program to forge linkages among the parents, schools, local businesses, and agencies.

The AAYP participants were students in fifth-grade classes in the 12 study schools (9 inner-city and 3 near-suburban) during the 1994–1995 school year or who transferred in during the study. Students who transferred out were not followed. Self-

Table 1. Observed Category Frequencies (%) for Substance Use by Group and Time

Category		0	1	2	3	4
$T1$ = 0 yr	Control n = 87	63 (72.4%)	14 (16.1%)	7 (8.05%)	7 (3.45%)	0
	Intervention n = 216	153 (70.8%)	31 (14.3%)	23 (10.7%)	9 (4.2%)	0
$T2$ = 0.5 yr	Control n = 82	43 (52.4%)	17 (20.7%)	10 (12.2%)	7 (8.6%)	5 (6.1%)
	Intervention n = 196	106 (54.1%)	37 (18.9%)	30 (15.3%)	15 (7.6%)	8 (4.1%)
$T3$ = 1.5 yrs	Control n = 103	52 (50.5%)	23 (22.3%)	10 (9.7%)	9 (8.7%)	9 (8.7%)
	Intervention n = 207	113 (54.6%)	35 (16.9%)	24 (11.6%)	20 (9.7%)	15 (7.3%)
$T4$ = 2.5 yrs	Control n = 89	27 (30.3%)	17 (19.1%)	20 (22.5%)	12 (13.5%)	13 (14.6%)
	Intervention n = 167	61 (36.5%)	33 (19.8%)	23 (13.8%)	23 (13.8%)	27 (16.2%)
$T5$ = 3.25 yrs	Control n = 86	18 (20.9%)	11 (12.8%)	12 (14.0%)	22 (25.6%)	23 (26.7%)
	Intervention n = 168	53 (31.5%)	35 (20.8%)	28 (16.7%)	25 (14.9%)	27 (16.1%)

report data were collected from the participating students at the beginning of fifth grade (pretest, T_1 = 0 year, n = 668), and through post-tests at the end of grades five (T_2 = 0.5 year, n = 634), six (T_3 = 1.5 year, n = 674), seven (T_4 = 2.5 year, n = 597), and eight (T_5 = 3.25 year, n = 645). The five waves of follow-ups resulted in a total sample of 1,153 African American students, of whom 571 were males. The mean age of these students was 10.8 years and 14.3 years in 1994 and 1998, respectively. The average household income for these students was \$10,000–\$13,000 in 1994, and \$15,000–\$18,000 in 1998. For the analyses in this article, we will focus only on the male students due to a lack of intervention effects among females on substance use behavior (Flay et al., 2004). In previous analysis of AAYP intervention effects on reducing substance use, similar effects of the two intervention groups, SDC and SC, were found (Flay et al., 2004). Therefore, and for simplicity of illustration of GMM, we combine the groups of SDC and SC as one intervention group. A total of 548 male students who participated in the AAYP study between 1994 and 1998 provided the data for this analysis. Among these students, 175 were in the control group and 373 were in the combined intervention group.

The substance use outcome behavior used in this study is a single ordinal scale (0 to 4) representing the number of substance use behaviors engaged in from four items: cigarette use, alcohol use, getting drunk or high, and marijuana use. Table 1 lists the observed category proportions from all five waves of data collection. For more details about the design and procedures of AAYP, please see Flay et al. (2004).

Results

Results from a conventional latent growth model, i.e., a one-class GMM, and a two-class GMM are listed in Table 2. In the model selection process, likelihood ratio tests were used to select the best mean- and covariance-structures for nested models with the same number of classes. For the one-class growth model, a linear growth with subject variations in both intercept and slope best fit the data. In deciding the best number of classes in a GMM model, it was shown by Tofighi and Enders (2006) and Nylund, Asparouhov, and Muthén (2007) that the Bayesian information criterion (*BIC*; Schwartz, 1978) and the sample-size adjusted *BIC* (*ABIC*; Sclove, 1987) are the most consistent indicators for a model with the correct number of classes. Therefore, in determination of the best GMM model, we first selected the best mean- and covariance-structures for two- and three-class GMMs, respectively. The final decision on the number of classes was made according to *BIC* and *ABIC*.

The results from the one-class growth model are in the left-hand column of Table 2. Notice that the first threshold was fixed at zero, and with the formulation of the cumulative logits model in (1) and (2), the negative estimate of β_0 revealed that control group subjects were more likely to respond in category 0 of the outcome (no substance use) at baseline. The mean intercept difference for the intervention group

TABLE 2. SUBSTANCE USE: PARAMETER ESTIMATES (STANDARD ERRORS)

	Model 1 Latent Growth Model	Model 2 Latent Growth Mixture Model	
		Class 1	Class 2
	$n = 548$	$n = 245$ (44.7%)	$n = 303$ (55.3%)
β_0: Intercept	-1.555 (0.315) *	0.064 (0.292)	-3.331 (0.839) *
β_1: Intervention	0.352 (0.345)	-0.200 (0.463)	0.948 (0.731)
β_2: Time	1.260 (0.150) *	0.222 (0.212)	2.070 (0.250) *
β_3: Time*Intervention	-0.328 (0.157) *	0.653 (0.333)	-0.912 (0.306) *
σ_I^2: Intercept Variance	4.457 (0.942) *	2.216 (0.806) *	3.729 (1.407) *
σ_{IS}: I-S Covariance	0.083 (0.257)	1.719 (0.525) *	0.083 (0.257)
σ_S^2: Slope Variance	0.426 (0.162) *	2.133 (0.972) *	-0.555 (0.423)
α_1: Threshold 1	0	0	
α_2: Threshold 2	1.497 (0.106) *	1.438 (0.473) *	
α_3: Threshold 3	2.905 (0.175) *	2.851 (0.485) *	
α_4: Threshold 4	4.569 (0.260) *	4.654 (0.529) *	
LogL	-1695.205	-1682.809	
Adjusted BIC	3421.991	3421.729	
Entropy		0.689	

*: p-value < 0.05

(β_1) was not significant, indicating success in randomization. The positive slope for the control group (β_2) was highly significant, meaning substance use among control subjects significantly increased over time. However, the intervention was effective in reducing that positive trend, as indicated by a negative β_3 ($p < 0.036$). For the random-effects variance parameters, although the Wald tests are questionable due to boundary issues (Bryk & Raudenbush, 1992, pp. 55), the ratio of an estimate to its standard error yielded values much larger than 2, indicating significant individual variations existed for intercepts and slopes. The covariance between the random intercept and slope (σ_{IS}) was close to zero.

In the selection of a best GMM, comparing the two-class and three-class models, lower values for *BIC* and *ABIC* suggested that two-class models fit the data better. In addition, a two-class GMM with class-specific covariance structures improved the model fit significantly over one with the same covariance structure for both classes ($\chi^2 = 20.86$, $df = 3$). To ascertain that the intervention group-condition did not affect class membership, we formally tested γ_{11} in equation (5). The result was not significant ($\chi^2 = 1.16$, $df = 1$), suggesting similar classification in both groups. It was suggested by Muthén et al. (2002) that the entropy measure summarizes the fit of classification in GMMs, with higher values indicating better classification. An entropy value of 0.69 (Table 2) from the two-class model for this study indicated reasonable classification.

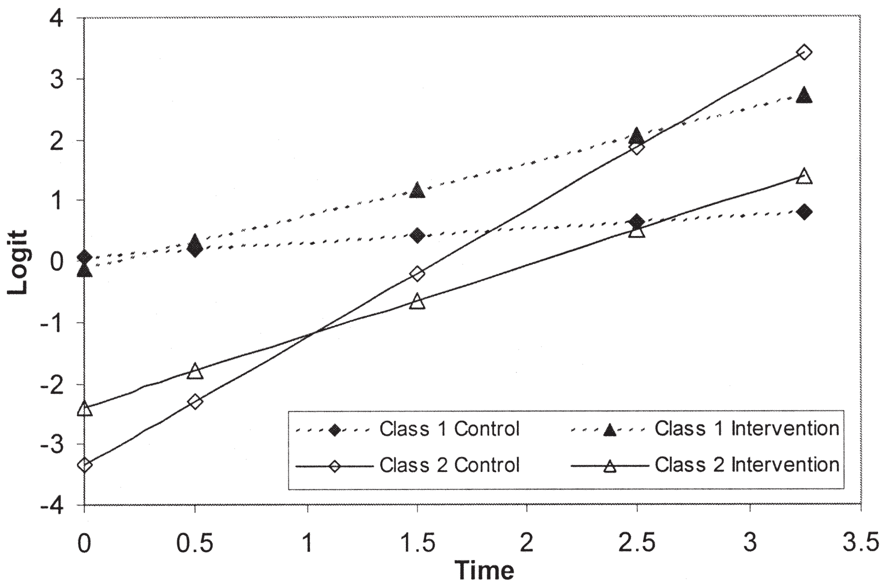
Results from the selected mixture model are listed in the right-hand columns of Table 2. Two distinct classes of growth trajectories with heterogeneous intervention effects were found. Class 1 consisted of 245 (44.7%) students, 74 (30.2%) in the control group and 171 (69.8%) in the intervention group. Class 2 had 303 (55.3%) students, 101 (33.3%) in control and 202 (66.7%) in intervention. Notice that the adjusted *BIC* was slightly lower for the two-class GMM, suggesting better fit. However, the GMM results revealed two distinct classes of growth trajectories and very different intervention effects. For Class 1, both the control group (β_2) and intervention group (β_3) had non-significant linear trends. Individual variances in intercept and slope existed for Class 1 subjects, with a positive covariance σ_{IS}. Turning to the results for Class 2, the mean intercept was significantly negative, suggesting lower odds of substance use at baseline among this class of students. The Class 2 control slope was positive and highly significant ($p < 0.0000$), while the intervention effect on the slope was significantly negative ($p < 0.0028$). This revealed that the intervention was effective for individuals with a potentially rapid increase over time. In terms of the random effect, individual variation existed in the intercept for Class 2, but not in terms of the slope. The covariance between intercept and slope was negative, but not significant.

Figure 2 presents the plot of the estimated mean growth from the two-class GMM. Again, Class 2 students had more profound increase over time, and the intervention was effective, while similar patterns of increase and intervention effect were not found for Class 1 students. Interestingly, Class 1 baseline levels were much higher than baseline levels for Class 2. Thus, our results suggest a beneficial intervention effect for students at low baseline levels, but not for those with relatively higher baseline levels.

DISCUSSION

In this study, we employed latent growth mixture modeling to a repeatedly measured categorical substance use outcome variable, which represents an advance beyond many other longitudinal studies of substance use behavior. By relaxing the single-population assumption in conventional growth modeling approaches, subgroups of growth trajectories were identified, revealing heterogeneous intervention effects among these different subgroups of the population. Data from the AAYP efficacy trial suggested two classes of adolescent substance use growth patterns: Class 1 started at a higher level and had a relatively shallow increase over

Figure 2. Estimated Mean Growths from 2-class GMM



time, individual variation was significant for both the intercept and slope, and the AAYP intervention was not effective for this class of adolescents. Class 2 had a lower baseline level with individual variation, a rapid increase over time without individual variation, and the intervention effectively reduced the increase of substance use for these adolescents. This finding suggested that the AAYP interventions on substance use were effective for rapid escalators or baseline nonusers, but were not effective for those students who were already users by baseline (grade 5). This suggests that effective prevention for early initiators needs to start in earlier grades. The Positive Action program is one example of a program that has shown effects on prevention of initiation of substance use (Beets et al., 2009). We note that this finding for substance use is distinct from an earlier finding for violence. Segawa et al. (2005) found that the program was effective for students already engaged in extreme violent behaviors at baseline and less so for students less engaged. These findings suggest that identification of growth profiles and heterogeneous intervention effects can certainly be helpful to researchers in determining the effectiveness or ineffectiveness of programs for particular subgroups of individuals and hence, lead to better targeting and improved interventions in the future.

The categorical outcome variable that we used in this study ranges from 0 to 4 and represents the number of substances endorsed. This kind of outcome could be treated as count data and a Poisson regression model with random coefficients could be employed. However, for this adolescent population with substance use behavior, too many zero counts existed for the distribution to satisfy the Poisson assumption (of equal mean and variance). For this situation, the Zero-Inflated Poisson (ZIP) model has been developed (Lambert, 1992) and extended to include random effects for longitudinal and/or clustered data (Hall, 2000; Hur, Hedeker, Henderson, Khuri, & Daley, 2002). The growth mixture extensions for the ZIP model are possibilities for future methodological research. In addition, the single- and two-class logistic models that were presented in this study assume the proportional odds assumption of covariate effect on the ordinal outcomes, as such an assumption is typically used in the logistic regressions in Mplus. The assumption can be tested by comparing models with and without covariate effects on the threshold values. Model constraints for this can be found in the Version 4 User's Guide.

The use of GMM with categorical variables is not without challenges. Categorical data inherently contain less variation than continuous data, which can make computation more difficult. Thus, it can be difficult to fit models with multiple classes of growth trajectories, each with distinct mean- and covariance structure. In fact, for the male substance use data we used in this study, convergence problems occurred for GMMs with more than three classes. In one three-class model that we were able to identify, the covariance structures for the three classes had to be constrained to be the same, which provided poor model fit. In addition to planning for a larger sample size when patterns of growth were to be investigated for discrete outcome variables, we found that when employing these kinds of models to examine the effect of a group condition, it can be helpful to first analyze the data by group to have a better understanding of the growth trajectories, as well as classifications within each group. Hence, when the combined data is formally analyzed, one will not be overwhelmed by a large number of possible model specifications to choose from.

In most social or behavioral research, mixture models have been employed for two purposes: to identify subgroups of individuals in the population or to approximate complex distributions. As cautioned by Bauer and Curran (2003) and Bauer (2005), it would be incorrect to interpret the classes found in the latter case as latent subgroups in the population, and it is critically important to consider both possible interpretations when applying such models. In this article, our goal was to reveal how intervention affects the behavior heterogeneously for different subpopulations. In the evaluation of intervention effects using GMMs, it is also important to ascertain that the intervention does not affect membership classifications so that the class-specific intervention effects can be attributed to the program. This assumption can be formally tested using the logistic prediction for class membership, with intervention as the covariate in equation (5). However, one should keep in mind that for the purposes of identifying true growth profiles in the population, important covariates could and should be able to affect classifications. Just as missing important covariate information may result in misleading estimates of regression coefficients, ignoring important covariates in GMM may result in misleading classifications of subgroups and their growth curves.

APPENDIX

Mplus program: Two-class growth mixture model for longitudinal substance use intervention.

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