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Dependent and problem drinking over 5 years: a latent class growth analysis ☆

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Abstract

Understanding the long-term course of problematic drinking is a fundamental concern for health services research in the alcohol field. The stability of, or change in, the course of drinking—especially heavy drinking—has both theoretical and applied relevance to alcohol research. We explore the application of latent class growth modeling to 5 years of survey data collected from dependent and problem drinkers—some not in treatment at baseline—in an attempt to uncover prototypical longitudinal drinking patterns. Results indicated that five profiles of drinkers can be used to represent their longitudinal course of alcohol consumption: early quitters ($N = 88$), light/non-drinkers ($N = 76$), gradual improvers ($N = 129$), moderate drinkers ($N = 229$), and heavy drinkers ($N = 572$). Significant baseline factors included ASI drug severity, dependence symptoms, and marital status. Attendance at AA meetings, the size of one's heavy drinking and drug using social network, past treatment, receiving suggestions about one's drinking, and contacts with the medical system were significant influences. The size of heavy drinking and drug using social networks was noticeably larger for the heavy drinkers. Findings also support the usefulness of a semi-parametric latent group-based approach as a tool for analyzing alcohol-related behaviors.

Keywords: Alcohol; Trajectories; Growth models; Risk factors; Longitudinal; Latent class growth models

1. Introduction

Understanding the long-term course of problematic drinking is a fundamental concern for health services research in the alcohol field. The stability of, or change in, the course of drinking—especially heavy drinking—has both theoretical and applied relevance to alcohol research (Kerr et al., 2002). Characterizing these courses can help us illuminate the underlying roles that a wide spectrum of factors play in the course of drinking—in getting better, staying the same, or progressing to more serious problems over time. A brief summary of the development of subtypes in alcohol consumption is provided by Jackson et al. (2000).

To address this issue and other research questions appropriate for a longitudinal design, the scientist has available a number of analytic options—many of only recent development. Each method may be more appropriate for different research questions, some methods overlap with each other, and many require a sophisticated approach. Overviews of some of the choices are given by Stoolmiller (1995), Windle (1997), Muthén and Muthén (2000), and Collins and Sayer (2001) among others. In related work we employed a hierarchal growth model to test the effects of various influences on the level of alcohol consumption over time (Weisner et al., 2003a; Matzger et al., in press). These influences included membership in groups such as those defined by gender and ethnicity. In such models those groups can be known a priori and these models can be thought of as modeling the "average" study participant. In the analysis reported here we focused instead on trying to uncover common or prototypical groups which are defined by their common pattern of

☆ Weights were created to account for differences in sampling fraction, fieldwork duration across agencies and non-response differences. We did not use them in this analysis although it is possible to include weights. Preliminary runs suggested using them resulting in little differences on these findings.

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drinking over 5 years. We asked: are there common drinking trajectories, what do they look like, and what appears to influence them?

The research reported here is part of an ongoing effort designed to follow a large representative sample of treated and untreated individuals with alcohol disorders drawn from the same community in an effort to understand alcohol consumption over time. Among its unique contributions is the inclusion of a probability sample of untreated individuals who met criteria for "problem drinking." It also includes a sample of people entering public and private chemical dependency programs in the same county with good response and follow-up rates.

Based on earlier work on this sample and the literature on long-term alcohol outcomes, we used a conceptual framework from longitudinal outcome research, including that of treatment careers and the natural course of treated populations (Hser et al., 1997; Joe et al., 1990; Simpson, 1990; Stoolmiller, 1995) plus the medical utilization literature (Aday et al., 1999; Andersen and Newman, 1973). We examined 5-year trajectories of profiles of drinking within a framework of *individual factors* (demographic and problem characteristics), *formal services* (substance abuse treatment and community agency contacts), and *informal influences* (12-step meeting participation and recovery-oriented social networks) (Bond et al., 2003; Weisner and Matzger, 2003; Weisner et al., 2003a).

1.1. Latent class growth models

To identify common drinking trajectories, we used latent class growth modeling (LCGM), an analytic approach based on finite mixture modeling (Muthén and Muthén, 2000; Nagin, 1999). We sought to characterize profiles of drinkers over time by constructing prototypical trajectories of the variable of interest—alcohol consumption.

The underlying assumption is that the collection of observed individual trajectories can be efficiently summarized by a smaller set of latent clusters of those trajectories. A rationale for approaching longitudinal data in this manner is provided by Nagin (1999) who uses the analogy of clinical diagnostic classifications; we know that not everyone with the same diagnosis is identical, but we also recognize that such groupings are meaningful and helpful in both clinical practice and research.

To illustrate, Fig. 1 displays several individual 5 year trajectories from our data which exemplify the wide variation in drinking patterns observed. Baseline levels varied, some increased the volume they drank over time, some drank less as time went on and some both increased and decreased how much they consumed. Thus, we cannot assume any change is necessarily monotonic.

The statistical method itself has a long history (Bauer and Curran, 2003) and has recently been developed by Nagin (1999), Nagin and Tremblay (2001), Roeder et al. (1999) as LCGM and in the context of structural equation modeling as

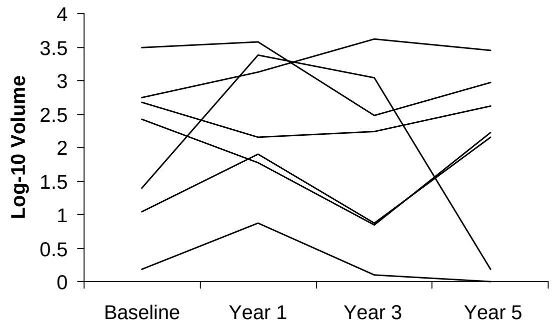

Fig. 1. Examples of drinking trajectories across 5 years.

growth mixture modeling (GMM) by Muthén and Muthén (2000). LCGM is a semi-parametric, group-based approach which uses a multinomial modeling strategy to identify homogeneous clusters of individual trajectories and to test the effects of covariates on those profiles. GMM is a multivariate normal method for reaching the same goal. While constrained, currently, to the multivariate case, GMM allows one to incorporate heterogeneity within the trajectories whereas LCGM does not. The LCGM approach, however, can be applied to a wider range of distributions of the dependent variable such as dichotomous indicators and counts.

In addition to estimating the number of latent profiles, one can test and fit separate polynomial terms to characterize the shape of each profile. It is also possible to test potential baseline factors which influence which latent profile an individual is assigned to as well as testing time-varying covariates which may influence the shape of each profile.

One important aspect of LCGM is that it provides an improvement on the "classify-then-analyze" procedure in which subjects are first classified to groups by some method such as a cluster analysis using a distance metric, and then the clusters are compared on various measures (e.g., Burgess et al., 2002). Such a method, in effect, assumes group/cluster membership is measured without error (Roeder et al., 1999). Not accounting for the error in cluster assignment in those comparisons may result in statistical bias. By *simultaneously* estimating group membership and testing for group differences, however, it takes the uncertainty of group membership into account in estimating the standard errors used in testing for differences.

A challenge to the application of this mixture-of-distributions approach is that there are many possible models to choose from with no clear, best procedure for searching among them. So determining the number of latent profile clusters, which and how many polynomial terms to include, and what baseline and covariate measures to include all form competing models. As a guide, Nagin advocates the use of Bayes factor to compare models (Kass and Raftery, 1995). Computed from the Bayesian information criteria (BIC), minus two times the change in BIC between models is an approximate Bayes factor which can then be used to select a parsimonious model. Reference to other criteria can be found in Bauer and Curran (2003) and Muthén (2003). LCGM has been used to date primarily in studies of adolescent behavior (e.g., Brame et al., 2001; Cote et al., 2002; Lacourse et al., 2002) where change is more the norm. In studies of drug use White et al. (2002) recently applied LCGM to adolescent smoking as did Colder et al. (2001) using GMM. Hill et al. (2000), Tapert et al. (2003), Chassin et al. (2002) and Oxford et al. (2003) used latent trajectories to study alcohol use among adolescents and Muthén and Muthén (2000) modeled heavy drinking using GMM.

We asked three primary questions: (1) are there underlying groups of prototypical profiles in the data; (2) what are the shapes of those profiles; and (3) are there variables, beyond drinking volume, which influence both which profile a subject is classified to and how the profile is shaped? Also, as this methodology has not yet been widely applied, we wanted to determine the feasibility of applying this approach to the field of alcohol research for questions such as these.

2. Method

2.1. Subjects

The study sample resulted from combining two sampling procedures. Details can be found in Weisner and Matzger (2002) and Weisner et al. (2002) and are summarized here. In-person interviews were conducted with individuals entering a county's public and private chemical dependency programs (the *treatment sample*) and with problem drinkers from the general county population (*general population sample*) who had not received treatment in the prior year. The *treatment sample* ($n = 927$) included consecutive admissions in the ten public and private programs in the county that met the following inclusion criteria (Kaskutas et al., 1997): (1) at least one new intake per week; (2) drugs other than alcohol were not the primary focus (e.g., methadone maintenance programs were not included); and (3) first line treatment entry (i.e., programs limited to aftercare or programs were excluded).

Data collection for the treatment sample was conducted by trained interviewers who were independent of the treatment agencies. They administered structured in-person questionnaires to all participants by the end of their third day of residential treatment or third outpatient visit. Informed consent was obtained and participation was independent of receiving agency services. The overall response rate for individuals in all programs participating in the study was 80%. The *general population sample* of dependent and problem drinkers not entering treatment ($n = 672$) was collected in the same county. Telephone interviews using random digit dialing methods were conducted with a probability sample of 13,394 individuals age 18 and over. Individuals were recruited for an in-person interview if they met problem drinking criteria (described below) and had not received substance abuse treatment during the previous 12 months.

Individuals met criteria for problem drinking by reporting at least two of the following during the previous 12 months: (1) drinking five or more drinks on a day at least once a month for men (three drinks on a day weekly for women); (2) one or more alcohol-related social consequences (from a list of eight); and (3) one or more alcohol dependence symptoms (from a list of nine). This measure is consistent with the predominant approach taken in research on alcohol epidemiology and similar measures have been used in a wide variety of published studies (Institute of Medicine, 1990; Schmidt et al., 1998; Weisner, 1990; Weisner and Schmidt, 1992; Wilsnack et al., 1991). Alcohol-related social consequences cover a range of ways that individuals with substance abuse problems come to the attention of others in the community (Hilton, 1987; Weisner, 1990; Weisner et al., 1995; Weisner and Schmidt, 1992). This included drinking–driving arrests, public drunkenness arrests, other alcohol-related criminal arrests, traffic accidents when drinking, other (non-traffic) alcohol-related accidents, and/or confrontations about an alcohol-related health problem by a medical practitioner, serious alcohol-related family problems caused by respondents' drinking, confrontations about an alcohol-related job problem by a supervisor or employer. The count of dependence items included nine criteria commonly used in clinical and general population research (American Psychiatric Association, 2000; Caetano and Weisner, 1995).

To select those individuals who met criteria for *alcohol dependence*, our measure consisted of a checklist of questions based on criteria from the Diagnostic Interview Schedule for Psychoactive Substance Dependence, DSM-IV (American Psychiatric Association, 2000) that has been used in other published studies (Humphreys and Weisner, 2000; Weisner et al., 2000a,b, 2001). We established whether each symptom was present or absent during the 30 days prior to the baseline interview.

2.2. Data collection

In-person baseline interviews were conducted in 1995 and 1996. One-, three- and five-year follow-up interviews were conducted using computer assisted telephone interviewing. Baseline respondents were tracked every three months using postcard mailings and telephone check-ins. Respondents who could not be reached by telephone were referred to a fieldwork agency for further searching. Follow-up response rates (based on the baseline survey) were 84% for year 1, 82% for year 3, and 79% for year 5.

2.3. Measures

The variables used in this analysis were selected based both on our previous research and selected for theoretical reasons (Hser et al., 1997; Weisner et al., 2003a). Also, these measures have been used in several published papers (Bond et al., 2003; Kaskutas et al., 2002; Weisner and Matzger, 2003; Weisner et al., 2003a). The behavior we sought to model was the change in the total number of drinks taken in the year prior to each assessment—the total volume of alcohol consumed. Given the skewed nature of the observed data, we used the base-10 log of the volume throughout the analysis. The resulting distribution fit much closer to the normal distribution and resulted in better fit statistics than the untransformed measure throughout our work with this data.

Baseline variables included age, gender, marital status, ethnicity, family income, alcohol-related social consequences, number of dependence symptoms, and whether respondents reported any alcohol treatment in the year prior to the interview. *Time-varying* measures covering the year prior to each interview included an indicator of whether they had received any suggestions about their drinking from anyone (family member or friend, as well as provider from a welfare, medical, criminal justice or workplace setting), whether they had any contact with any community agency system (i.e., welfare, medical, criminal justice, workplace) about their drinking, the size of their heavy drinking and drug using social network, the number of days they attended an AA meeting, and whether they had received any substance abuse treatment (Cote et al., 2002).

2.4. Procedure

The literature suggests that those whose problems are more severe may have less reduction in consumption and problems over time and those whose problems are less severe are at less risk for having their problems addressed or entering treatment (Finney and Moos, 1992; Shaw et al., 1997; Simpson, 1990; Simpson et al., 2002). However, it is unknown if this would effect the latent classifications so instead of modeling dependent and non-dependent respondents separately we tested baseline dependence as one of the candidate variables.

Given the very large set of possible models and the lack of a fully objective method of model selection, we proceeded with model building and testing in four steps: (1) estimating the number of profiles; (2) screening for candidate baseline variables; (3) screening for time-varying covariates; and (4) testing a final model. To implement the work we employed a user-written SAS procedure, Proc Traj (Jones et al., 2001).

More specifically, in the first step, five different latent class growth models of alcohol volume were estimated: the first fitting only two latent profiles, the next three profile groups, and so on up to a model with six latent profiles. Each model contained no covariates but did include terms for linear and quadratic time effects—a decision based on the examination of the data (see Fig. 1) and the four-time point design. Using the Bayes Factor as a guide to compare model fit, we selected the most parsimonious model. Part of this decision included the relative size of each resulting profile so that, ideally, no one cluster held less than approximately 5% of the total sample.

Second, once the optimal number of latent profiles was established, we screened among the baseline variables for candidates to add to the model using a method similar to the model-building strategy discussed by Hosmer and Lemeshow (1989) for logistic regression (p. 86) and Nagin (1999). To do this, a multinomial logistic regression model, with predicted latent profile group membership from the first step as the dependent variable and the candidate baseline variables as covariates was estimated and tested. All candidate predictors with $P < 0.10$ were kept and placed in a new latent trajectory model. We then re-fit the latent trajectory model, again constraining it to have the same number of profiles found optimal in step one, but now including the baseline variables selected through the screening. This provided us with a test of each of the candidate baseline variables. For the next step, we retained only those baseline variables which were statistically significant. By adding the baseline variables to the model, some subjects may be assigned to a different latent profile.

In the third step the—estimated latent profile group membership from step 2 was used in a second screening analyses—this time to select candidates from among the time-varying covariates. Given that each covariate was measured four times (once per assessment), we used a set of repeated measures general linear models for the screening—one per candidate measure—in place of a single multinomial logistic regression. Measures where the profile-by-time interaction was significant were retained for inclusion in the final model. Then, in the forth and final step, a model was estimated and tested which now included both the baseline variables and the time-varying covariates.

3. Results

In comparing model fit among the two-class (BIC $= -6558.29$), the three-class (BIC $= -6432.63$), the four-class (BIC $= -6328.72$), the five-class (BIC $= -6261.71$), and the six-class (BIC $= -6496.08$) models, a five-latent profile model was selected. The probability of correct model for the five-class solution was equal to 1.0 (Nagin, 1999, formula 6). Examination of the mean posterior probabilities of assignment to profile are displayed in Table 1 and indicate a strong separation among the profiles.

Table 1
Mean posterior probability of latent profile group membership (row) by latent profile group assigned to (column)

	Early quit	Non-drinkers	Gradual improvers	Moderate drinkers	Heavy drinkers
Group 1	0.96	0.01	0.01	0.01	0.00
Group 2	0.00	0.96	0.00	0.01	0.00
Group 3	0.01	0.00	0.89	0.02	0.00
Group 4	0.03	0.03	0.07	0.82	0.10
Group 5	0.00	0.00	0.03	0.15	0.90

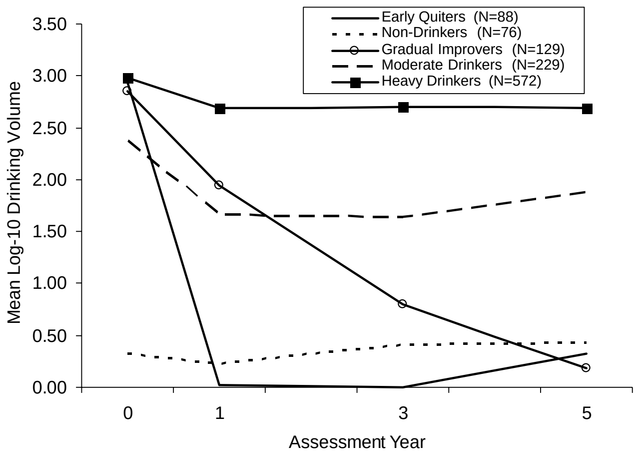

Fig. 2. Latent group profiles of mean log 10 number of drinks consumed in the prior year.

For descriptive purposes we labeled the latent profiles, displayed in Fig. 2, as early quitters ($N = 88$), light/non-drinkers ($N = 76$), gradual improvers ($N = 129$), moderate drinkers ($N = 229$), and heavy drinkers ($N = 572$). That is not to say respondents assigned to the moderate drinkers profile, for example, were all drinkers at all time points. The proportion in each group who reported no drinking in the previous year, as shown in Table 2, however, suggests these labels are reasonable.

Table 3 displays the parameter estimates and tests of significance for the final modeling step. Though not displayed in the figures, the predicted latent group profiles were close to the observed.

As in any longitudinal study, survey respondents dropped out of the study for various reasons or did not answer all baseline questions resulting in missing data. As this methodology requires full data to estimate the latent trajectories, this analysis was run on a final sample size of 1094. The question then is whether a model including the missing cases, had they been available, would have resulted in a different solution. There is no way of knowing that or how the dropouts are distributed among the five latent classes. Comparisons on baseline measures between those with full data and those without found some statistical differences. Those without full data were more likely to be male, have higher ASI psychiatric, drug and employment severity scores, less ASI alcohol severity, more AA attendance, and smaller sized drinking networks (all $P < 0.05$).

Table 2
Proportion of group membership reporting no drinks consumed in prior year

	Baseline	Year 1	Year 3	Year 5
Early quit	0.0	96.6	100	77.3
Non-drinkers	67.1	76.3	65.8	65.8
Gradual improvers	0.0	13.2	48.1	73.6
Moderate drinkers	1.3	16.2	13.5	4.8
Heavy drinkers	0.17	1.6	0.7	0.5

We also used a variation on multiple imputation to address this matter. Proc MI in SAS was employed to generate five imputed datasets using MCMC. For each of the imputed datasets we re-estimated a five-class model and cross-classified group membership in one model against another's. For each of the resulting ten contingency tables, we computed the percentage of respondents not assigned to the same profile in both models. The average discordance was only 11.6% with the majority of that resulting from switching between the heavy and moderate trajectories. This is consistent with the off-diagonal mean posterior probabilities seen in Table 1.

3.1. Profile shape

As expected, given the study recruitment methods, all profiles (Fig. 2) begin at a high level of drinking with one exception. The light/non-drinkers are characterized by relatively little drinking throughout the 5-year period. In reviewing the data it appears that these participants were, at the time of their baseline interviews, in treatment for drug problems other than alcohol. The fact that this group was separated out supports the usefulness of the LCGM approach to modeling trajectories.

The early quitters are mainly respondents who went from heavy drinking to a very low level of alcohol consumption and maintained that low level with a rise in year 5. The gradual improvers displayed a steady drop in mean alcohol consumption over time. In contrast, both the moderate and heavy drinker groups continued their consumption across time. The moderate drinker group, however, began at a lower level at baseline (a profile group mean of 1.7 drinks per day versus 4.5 for the heavy profile) and appeared to have declined more at year 1. The difference in consumption is striking. The mean number of drinks for the moderate drinkers at year 1 is down to 0.8 drinks per day while it only dropped to a mean of 3.2 drinks per day for the heavy drinkers. Also of note is that the heavy drinkers form the largest group ($N = 572$, or 52.3% of the sample).

3.2. Baseline variables

Among the baseline variable candidates, ASI drug severity, number of dependence symptoms, family income, and marital status (constructed as two contrasts comparing those never married to those formerly married and to those currently married) all passed the screening step. In testing these four variables among the five latent profiles, only family income was not significant. Then light/non-drinkers and gradual improvers had the highest mean ASI drug severity scores at intake (0.14 and 0.11) while the heavy drinkers had the lowest (0.05). Interestingly, the early quitters had the highest number of dependence symptoms (mean = 5.23) and the light/non-drinkers had the lowest (0.08).

Table 3
Estimates, standard errors and tests of significance of the final model for the problem drinking sample

Group	Parameter[a]	Estimate	Standard error	*T*-value	*P* > |*T*|
Baseline variables					
Non vs. early	Constant	2.57	0.355	7.23	0.0000
	ASI drug	8.55	2.120	4.03	0.0001
	Dependence Sx	−3.64	0.563	−6.48	0.0000
	Formerly married	−0.14	0.311	−0.46	0.6440
	Married	0.61	0.307	2.00	0.0459
Decliners vs. early	Constant	0.40	0.348	1.15	0.2522
	ASI drug	2.21	1.279	1.73	0.0838
	Dependence Sx	−0.05	0.062	−0.82	0.4123
	Formerly married	−0.62	0.216	−2.87	0.0042
	Married	0.41	0.227	1.81	0.0698
Moderate vs. early	Constant	2.76	0.316	8.73	0.0000
	ASI drug	0.90	1.407	0.64	0.5208
	Dependence Sx	−0.48	0.068	−7.03	0.0000
	Formerly married	−0.63	0.211	−2.98	0.0029
	Married	0.23	0.218	1.04	0.2998
Heavy vs. early	Constant	3.03	0.282	10.73	0.0000
	ASI drug	−1.86	1.176	−1.58	0.1147
	Dependence Sx	−0.25	0.051	−4.84	0.0000
	Formerly married	−0.63	0.172	−3.65	0.0003
	Married	0.32	0.189	1.68	0.0939
Time-varying covariates					
Early quitters	Intercept	2.43	0.250	9.75	0.0000
	Linear	−5.10	0.422	−12.10	0.0000
	Quadratic	0.91	0.082	11.06	0.0000
	AA meetings	0.00	0.001	2.31	0.0212
	Network size	0.01	0.015	0.60	0.5468
	Prior Txt	0.51	0.222	2.29	0.0222
	Suggestions	0.18	0.129	1.42	0.1570
	Contacts	−0.08	0.091	−0.91	0.3638
Non-drinkers	Intercept	−0.35	0.225	−1.54	0.1239
	Linear	0.10	0.139	0.74	0.4596
	Quadratic	−0.01	0.024	−0.25	0.8020
	AA meetings	−0.01	0.001	−4.70	0.0000
	Network size	0.07	0.017	4.08	0.0000
	Prior Txt	0.12	0.177	0.65	0.5153
	Suggestions	0.06	0.114	0.57	0.5686
	Contacts	0.03	0.074	0.42	0.6758
Decliners	Intercept	2.06	0.128	16.08	0.0000
	Linear	−0.65	0.100	−6.49	0.0000
	Quadratic	0.02	0.021	0.92	0.3555
	AA meetings	0.00	0.001	−2.41	0.0160
	Network size	0.03	0.007	4.23	0.0000
	Prior Txt	0.88	0.112	7.82	0.0000
	Suggestions	0.17	0.087	1.90	0.0573
	Contacts	0.03	0.059	0.51	0.6099
Moderate	Intercept	2.23	0.089	25.01	0.0000
	Linear	−0.48	0.067	−7.09	0.0000
	Quadratic	0.08	0.013	6.47	0.0000
	AA meetings	−0.02	0.002	−10.95	0.0000
	Network size	0.05	0.010	4.81	0.0000
	Prior Txt	0.12	0.102	1.19	0.2339
	Suggestions	0.37	0.088	4.21	0.0000
	Contacts	−0.06	0.043	−1.46	0.1450

Table 3 (*Continued*)

Group	Parameter[a]	Estimate	Standard error	*T*-value	$P > \|T\|$
Heavy	Intercept	2.87	0.049	59.06	0.0000
	Linear	−0.17	0.036	−4.60	0.0000
	Quadratic	0.03	0.007	3.77	0.0002
	AA meetings	0.00	0.001	−4.71	0.0000
	Network size	0.01	0.003	4.09	0.0000
	Prior Txt	0.29	0.057	5.05	0.0000
	Suggestions	0.22	0.045	4.97	0.0000
	Contacts	−0.07	0.026	−2.80	0.0051

BIC = −5704.4 ($N = 1094$).

[a] ASI drug: alcohol severity index drug severity; dependence symptoms: number of dependence Sx; formerly married: formerly vs. never married; married: married vs. never married; contacts: contacts with formal services; AA meetings: number of AA meeting attended in previous year; network size: number of heavy drinking and drug using individuals in respondents social network; prior Txt: received treatment for alcohol dependence in prior year; suggestions: received suggestions about their drinking from anyone.

3.3. *Time-varying covariates*

The number of AA meetings, drinking cohort size, treatment in the past year, receiving suggestions from others and contacts with the medical system were retained by the screening procedure for testing. Plots of the means for each of these four covariates over time for each of the five latent profile groups are shown in Fig. 3.

The means for the moderate and heavy drinkers track in a consistent fashion, with the exception of the size of the drinking cohort which is larger for the heavy drinkers. The early quitters had the highest AA attendance at year 1 and the gradual improvers had the highest number of suggestions received throughout.

4. Discussion

These results indicate that the course of drinking over a 5-year period is variable and influenced by several factors. Yet, while there appears to be substantial variation, a limited number of prototypical profiles emerged. From the standpoint of health services research, the single dominant profile—the largest group which did not appreciably change drinking consumption—is an important finding. In their review of studies of the stability of alcohol consumption over time, Kerr et al. (2002) point out that the question of the stability of consumption is key to questions of mortality and diseases attributable to heavy consumption.

While this is the first LCGM of this sample and requires replication, these findings suggest that dependent and problem drinkers may be, initially, divided into two general categories: those that continue to drink at a steady pace over time (i.e., the heavy and moderate drinking) and those for whom their drinking declines. More effort on understanding who comprises the "stable" group is clearly needed. The tests of the baseline measures suggest those who substantially reduced their drinking were most likely to be those who were the most heavily dependent at baseline. This may be driven to some degree by regression to the mean.

The covariates indicate that, in general, those who had gone to fewer AA meetings and those who had received fewer suggestions about help for their drinking were less likely to have been in treatment, and were more likely to display a steady level of drinking over time. The apparent influence of the size of one's cohort of heavy drinkers and drug users can also be seen in these findings.

The results found here are in agreement with and compliment the analysis of Weisner et al. (2003a) who found that in addition to treatment status and formal influences, recover-oriented social networks are key influences on lower levels of drinking. They expand upon those results by describing the underlying common patterns of that drinking. Such patterns cannot be identified by the more common mixed-effects repeated measures analysis.

In preliminary analyses we noticed continuing improvement in model fit as models with greater numbers of cluster profiles were applied to the data by splitting out respondents from the heavy and moderate drinking groups into smaller groups. This may indicate that this large group of steady drinkers have a common pattern of steady consumption, varying only in their level of how much they consume. Such a notion is supported by the mean group probabilities just off the diagonal in the lower right corner of Table 1 and the variations seen among the multiply-imputed model results.

The continuing improvement in model fit as the number of latent profiles is increased has been discussed by Nagin and Tremblay (2001) and Bauer and Curran (2003). This reflects a basic statistical problem that if the underlying distribution of profiles is not distinct but continuous, one is attempting to approximate that continuity by a discrete function. However, the distinction between those two groups may be important if the relationship between amount of alcohol consumed and health-related consequences is non-linear such that the adverse consequences accelerate once some level of daily drinking is surpassed.

As in any research, this study has some limitations including the use of a sample drawn from a single US county's population and the reliance on self-report. The county was chosen to be representative; it was selected on the basis of

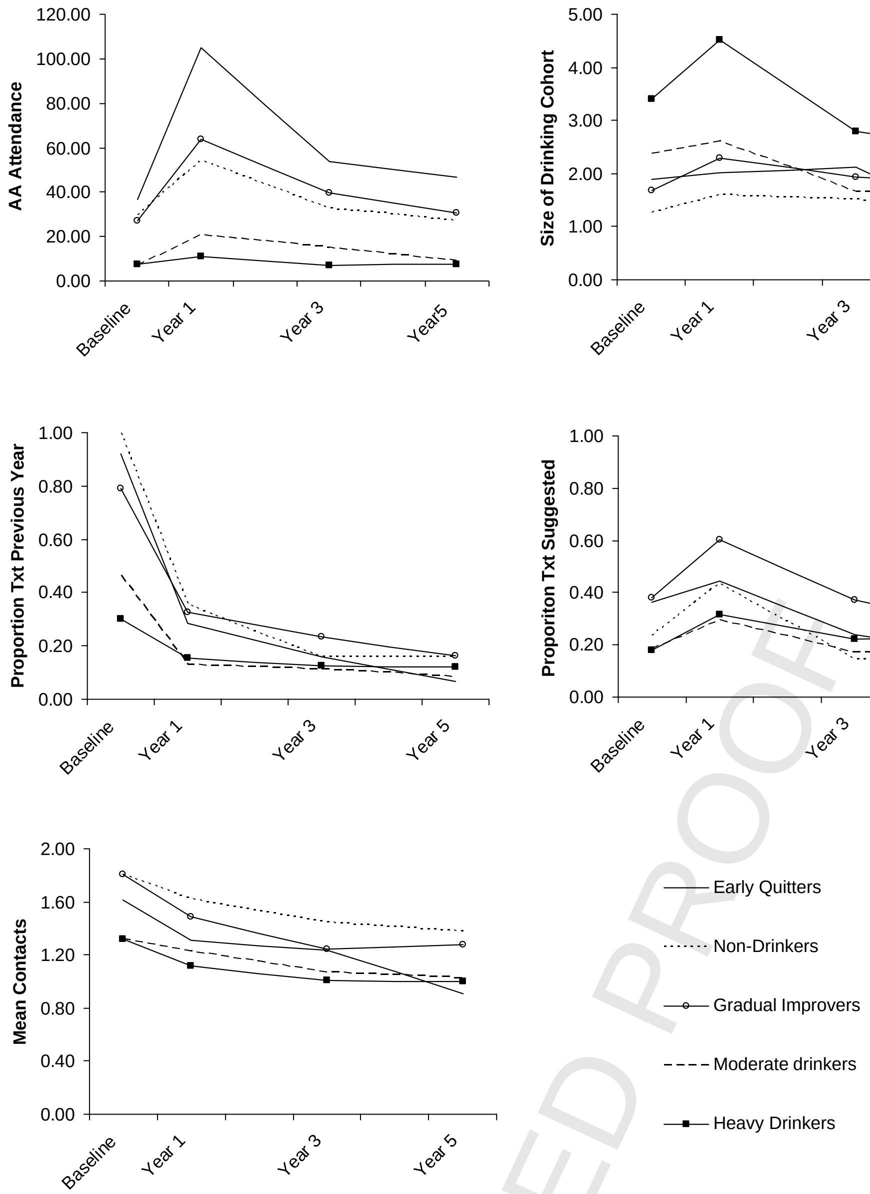

Fig. 3. Plots of time-varying covariate means by latent group over time. Legend for all plots in low left plot.

diversity in its population characteristics and mix of rural and urban areas. For the self-reports the study used robust questions and well-established interview techniques developed through the Community Epidemiology Laboratory and clinical studies. Both of these issues are discussed further in Weisner et al. (2003a).

Complete baseline and alcohol consumption data at each assessment required the deletion of some respondents' data (time-varying covariates, however, could be missing). If the data are missing completely at random, then we suffered a loss of statistical power. If not, the latent structure may be different had those missing cases not been lost. While some differences were found between those not in the analysis and those retained as indicated previously, the differences were not, on the average, substantial (i.e., small sized effects—most less than $d = 0.20$). Also, the lack of variation in results from one imputation to another, except for the mixing between the heavy and moderate drinking groups, argues for the generalizability of the groupings.

As with any new and complex method, the application of it can be daunting and has some limitations as pointed to in Nagin (1999). The analysis can be somewhat time consuming both in time to choose and test the appropriate models and, to a lesser extent, in computer time. A number of possible models were not tested and the method of model selection may have allowed a more parsimonious model to be missed. Not all data will provide a clear point at which to set the number of profiles to fit. It may be difficult for the iterative process to find a maximum likelihood solution, the algorithm is sensitive to starting values, and respondents missing baseline factors are not included in the analysis. While the use of the change in BIC decreases the subjectivity in model selection, more objective help would be welcomed. Also methods for selecting candidate baseline and time-varying covariates could be extended.

Further, by approaching this modeling through the semi-parametric LCGM approach over the parametric GMM method, we were forced to use a more cumbersome model selection procedure. GMM is applicable to this data because we used a response variable, log volume, which is normally distributed. We chose the LCGM approach for three reasons. First, there are other non-normally distributed measures we are interested in such as alcohol abstinence and AA attendance. As this time, GMM is restricted to the multivariate normal case. Second, as this method has seldom been used in this arena (and not on a sample such as this) we were not certain we would have sufficient data to estimate within-class heterogeneity or that it would be informative. Finally, we have been working in SAS and this Proc is available at no cost.

The broader case for using methods such as LCGM in this context is discussed by Muthén and Muthén (2000). It has been successfully used in the field of adolescent behavior by Nagin and colleagues and appears well suited for an application such as this. The results, at least in these data, are useful and interpretable. The ability to detect and describe underlying common longitudinal trajectories should help bring greater insight to understanding behavioral changes over time as serve as a complimentary method to the more standard mixed-effects ANOVA approach to longitudinal data. Nagin and Tremblay (2001) have extended LCGM to modeling separate but related outcomes and version 3 of Mplus promises several improvements (http://www.statmodel.com/mixtureaddon.html). In general, LCGM and GMM, as well as longitudinal studies using more than only two time points (Fillmore, 1988) will benefit alcohol and drug abuse research in the future.

Uncited references

Kaskutas (2001), Weisner et al. (2003b).

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