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Lapses following Alcohol Treatment: Modeling the Falls From the Wagon*

Katie Witkiewitz, PH.D.[†]

University of Washington, Box 354805, 1107 NE 45th Street, Suite 120, Seattle, Washington 98105-4631

Abstract

Objective—This study investigated transitions between drinking and nondrinking during the first 12 months following treatment and whether transitions in posttreatment drinking are related to alcohol-dependence symptoms.

Method—Data from individuals in the outpatient ($n = 952$) and aftercare ($n = 774$) arms of Project MATCH (Matching Alcoholism Treatments to Client Heterogeneity) were included in the analyses. Drinking consequences, percentage of drinking days, and drinks per drinking day were used as indicators of drinking behavior. Latent transition analysis was used to estimate a model of drinking patterns, defined by transition probabilities between drinking classes, from immediately following treatment to 6 and 12 months following treatment.

Results—Across both aftercare and outpatient samples, three drinking classes were identified at each time point: frequent heavy drinking with high consequences, moderate infrequent drinking with low consequences, and nondrinking with low consequences. Many participants maintained nondrinking, and, of those who drank, there was a trend toward transitioning to less drinking over time. Transition probabilities were noninvariant across treatment arms: The probability of transitioning from moderate drinking to frequent drinking was more than six times more likely in the aftercare arm, as compared with the outpatient arm. In both samples the transition to heavy drinking and membership in the heavy-drinking class were significantly positively related to alcohol-dependence symptoms. There were no differences across MATCH treatment groups.

Conclusions—This study examined transitions in post-treatment drinking and the role of alcohol dependence in predicting posttreatment drinking. The results suggest a low probability of moderate drinking among individuals with greater alcohol dependence.

The world health organization (2002) has estimated that approximately 76.3 million people worldwide have diagnosable alcohol-use disorders. In the United States, roughly 17.6 million people meet criteria for an alcohol-use disorder (Grant et al., 2004), and only 12.5% of those who meet criteria receive treatment for an alcohol problem (Stinson et al., 1998). Among individuals who receive treatment, 65% to 90% have at least one drink, or a lapse, in the first year following treatment (Maisto et al., 2003; Sutton, 1979). The high rates of lapses following treatment have led researchers to question the effectiveness of treatments (Miller and Wilbourne, 2002), to develop alternative definitions of outcomes (Maisto et al., 2003), and to prescribe aftercare following treatment (McKay et al., 2005).

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[†]Correspondence may be sent to Katie Witkiewitz at the above address or via email at: E-mail: kate19@u.washington.edu.

Several studies have demonstrated the importance of early abstinence immediately following treatment (Booth, 2006; Carroll et al., 2000; Elal-Lawrence et al., 1987; Moos and Moos, 2006; Stout, 2003). Stout (2000) concluded that 1, 2, or 4 weeks of continuous abstinence predicted greater long-term success. Booth (2006) reported that early abstinence of 15 weeks or more played an important role in those with successful outcomes (e.g., sustained reduction in drinking quantity, frequency, and related consequences). One question that remains is whether continuous abstinence immediately following treatment is necessary for a successful outcome or whether an individual may experience a lapse following treatment and then return to abstinence or moderate drinking. Based on the cognitive-behavioral model of relapse, it has been hypothesized that a lapse often is a learning opportunity that may help a person cope more effectively with high-risk situations in the future (Carroll, 1996).

Consistent with this idea, recent conceptualizations of the relapse process have defined *posttreatment alcohol use* as a dynamic process, whereby individuals cycle and recycle through drinking and nondrinking states (Hufford et al., 2003; Witkiewitz and Marlatt, 2004). This dynamic often had been observed clinically but had not been tested empirically. Likewise, the question of whether early lapsing still can lead to long-term successful outcomes (moderate drinking or abstinence) had not been tested. Furthermore, the question of whether moderate drinking is even a viable goal for those who are severely alcohol dependent is hotly debated (see Sobell and Sobell, 1995). Some studies concluded that individuals who are severely dependent are able to maintain moderate drinking (Heather et al., 2000; Miller et al., 1992). Other studies, however, showed that alcohol dependence predicts more rapid reinstatement of alcohol use after a period of abstention (Babor et al., 1987) and worse outcomes (increased drinking quantity and frequency) following the initial lapse (Witkiewitz and Masyn, in press). The goal of the current study was to gain a better understanding of posttreatment drinking by studying transitions between drinking and nondrinking states, as well as the relationship between alcohol dependence and drinking states during the first year following treatment.

Quantifying patterns of alcohol use and predicting post-treatment drinking has been a goal of addictive behaviors researchers for nearly 30 years (Sutton, 1979). Over the past decade, methodology has been developed that provides opportunities for applying advanced statistical methods to identify variability in substance-use patterns across individuals as a function of time and covariates (Hser et al., 2001; Maisto and Connors, 2006; McKay et al., 2006; Muthén and Muthén, 2000; Stout, 2007). One method, latent growth mixture modeling (LGMM), is a longitudinal-data analytic technique that combines finite mixture modeling with a latent growth-curve model. It has increasingly been employed by addictive behaviors researchers (Jackson et al., 2006; Muthén and Muthén, 2000; Windle et al., 2005).

A previous application of LGMM to the study of post-treatment drinking in the Project MATCH (Matching Alcoholism Treatments to Client Heterogeneity) data (Project MATCH Research Group, 1993) identified three common drinking trajectories, described as (1) continuously heavy drinkers, (2) drinkers who initially drank heavily and then returned to light drinking or nondrinking, and (3) light drinkers or nondrinkers. The results from that study supported theoretical descriptions of the relapse process. Erratic drinking patterns in the sample, however, were not explained by the model (see Witkiewitz et al. [2007], Figure 1b, p. 379). LGMM estimates variability based on continuous drinking patterns and cannot account for discontinuous changes in behavior. Thus, when individuals transition from frequent to infrequent drinking (i.e., have discontinuous trajectories), the change in drinking is considered error (or misclassification) by the model.

Latent transition analysis (LTA) has the potential to provide an analysis of discontinuous drinking trajectories by estimating initial drinking status and the probability of jumping

between drinking states (Böckenholt, 2005; Dolan et al., 2005; Velicer et al., 1996). By assuming a latent transition process, the shifts from one drinking state (or class) to another can be described in probabilistic terms using latent transition probabilities (Böckenholt, 2005). LTA, which is based on latent class theory (Goodman, 1974; Lazarsfeld and Henry, 1968), already has been shown to be useful in estimating transitions to heavy drinking among young adults (Auerbach and Collins, 2006); in estimating the likelihood of developing alcohol dependence in adulthood (Guo et al., 2000); and in assessing the effectiveness of a substance-misuse prevention program (Graham et al., 1991).

By constraining certain parameters, LTA can be used to test several aspects of the data. The current study was designed to determine whether the heterogeneity in drinking behavior following treatment can be explained by discrete drinking states and transitions between drinking states. Specifically, analyses were conducted to address four research questions:

1. Is drinking behavior, as indicated by drinking frequency, quantity, and drinking-related consequences, homogeneous across participants? Based on previous studies of treatment outcomes, it is hypothesized that individuals will display significant heterogeneity in their drinking behavior across time (e.g., Russell et al., 2004).
2. Assuming heterogeneity in drinking behavior at each time point, is there movement between latent drinking classes? Based on previous conceptualizations of relapse and empirical data (Miller, 1996; Witkiewitz et al., 2007), it is hypothesized that drinking behavior will be discontinuous across time, such that individuals may be 100% abstinent one month and 0% abstinent the next month (the “fall from the wagon”) or 0% abstinent one month and 100% abstinent the next month (e.g., “quantum change”; Miller and C’de Baca, 2001).
3. Are drinking states and transitions between drinking states invariant across treatment settings or type of treatments received?
4. Considering previous research on the relationship between alcohol dependence and posttreatment drinking outcomes (Babor et al., 1987; Moos and Moos, 2005), does alcohol-dependence severity relate to drinking states and movement between drinking states across time? It is hypothesized that participants with more alcohol-dependence symptoms will be unlikely to maintain moderate drinking and will be more likely to transition from nondrinking to heavier or more frequent drinking (Babor et al., 1987).

Method

Participants

The data for this study are from the multisite, randomized clinical trial of alcohol treatment matching known as Project MATCH (Project MATCH Research Group, 1993). The trial recruited 1,726 participants with alcohol-use disorders and randomly assigned them to three individually delivered treatments: (1) cognitive-behavioral therapy (CBT; Kadden et al., 1992); (2) motivational enhancement therapy (MET; Miller et al., 1992); and (3) twelve-step facilitation (TSF; Nowinski et al., 1992). Project MATCH recruited subjects for outpatient and aftercare programs at nine clinical research sites across the United States. In the outpatient arm ($n = 952$), participants were recruited from the community or outpatient treatment centers. In the aftercare arm ($n = 774$), participants were recruited from intensive day-hospital or inpatient-treatment centers.

On meeting inclusion and exclusion criteria, participants were given an intake diagnostic evaluation, which consisted of (1) demographic history; (2) alcohol, drug, and psychotic screen sections of the Structured Clinical Interview for DSM-III-R (SCID; Spitzer and Williams,

1985); (3) estimates of alcohol consumption via the Form 90 (Miller and Del Boca, 1994); (4) legal, psychiatric, and family history sections of the Addiction Severity Index (McLellan et al., 1992); and (5) psychological evaluation of mood, sociopathy, and social support. After providing informed consent and completing intake assessments, participants were then randomized to one of three treatments (CBT, MET, and TSF). Follow-up assessments were conducted immediately after treatment and 6, 9, 12, and 15 months after the first therapy session. A comprehensive list of all follow-up assessments can be found in previous Project MATCH publications (Project MATCH Research Group, 1993, 1997). For the current study, measures were used from the initial post-treatment assessment and the 6- and 12-month assessments following treatment. Measures relevant to the current study are described below.

Measures

The reliability and validity of the measures used in Project MATCH were adequate (see Connors et al., 1994; Del Boca and Brown, 1996; Project MATCH Research Group, 1997). Self-reported drinking data were corroborated via collateral informants and biochemical measures. For interview data, the intraclass correlations between raters were high.

Drinking consequences—The Drinker Inventory of Consequences (DrInC; Miller et al., 1995) was used to assess consequences experienced as a result of drinking in the last 3 months. The DrInC asks respondents to report on a 4-point Likert-type scale (0 = never, 3 = daily) how frequently they have experienced each of 45 drinking consequences, with higher DrInC scores indicating more consequences. For the current study, DrInC scores were divided into three categories: (1) few or no consequences (DrInC score < 10); (2) medium consequences (DrInC score = 10–39); and (3) high consequences (DrInC score ≥ 40). This categorization was based on the distribution of DrInC scores, as well as previous mixture analyses of the DrInC measure (Wu and Witkiewitz, 2008).

Drinking quantity—Drinks per drinking day (DDD) were assessed using the Form 90 (Miller and Del Boca, 1994). The primary goal of the Form 90 interview is to gather information regarding a person's drinking behavior over a 3-month (90-day) period using a calendar method, such that data can be summarized weekly or monthly during the assessment window. For the current study, DDD over the previous 30-day period was categorized into (1) *nondrinking*, defined as zero DDD; (2) *moderate drinking*, defined as five or fewer DDD for men or four or fewer DDD for women; and (3) *heavy drinking*, defined as more than five DDD for men and more than four DDD for women. This categorization was based on the definition of *heavy drinking* provided by the National Institute on Alcohol Abuse and Alcoholism (2004).

Drinking frequency—Percentage of drinking days (PDD) also was derived from the Form 90 instrument (Miller and Del Boca, 1994). In the current study, PDD was categorized into (1) *nondrinking*, defined as 0% drinking days in the 30 days before assessment; (2) *infrequent drinking*, defined as drinking on <50% of the days in the 30 days before assessment; and (3) *frequent drinking*, defined as drinking on ≥50% of the days in the 30 days before assessment. Alternative definitions of *infrequent drinking* were considered (e.g., <30% days abstinent = infrequent drinking). An inspection of the distribution of drinkers who drank at least once at each time point, however, demonstrated strong bimodality with a local minimum at 50%. The average (SD) PDD of those included as infrequent drinkers ranged from 17% (12%) to 24% (11%), whereas the average PDD of frequent drinkers ranged from 84% (17%) to 88% (15%).

Alcohol dependence was defined as the number of current alcohol-dependence symptoms (range: 0–9), based on the SCID (Spitzer and Williams, 1985) administered before treatment.

Data analyses

The software program Mplus Version 5 (Muthén and Muthén, 1998–2007) was used to estimate all latent class and transition models. For the current study, the analyses proceeded in several stages. First, measurement models of drinking-outcome indicators were estimated at each time point for each treatment arm. Second, cross-sectional patterns of drinking classes and response frequencies for each drinking-outcome indicator were evaluated for each treatment arm. Third, several latent transition models were estimated to test the assumption of invariant transition probabilities across treatment arms. Fourth, latent transition models were estimated to examine the effect of treatment assignment on drinking classes and transition probabilities across time. Finally, a model that incorporated alcohol dependence as a time-invariant covariate predicting drinking-class membership and transitions between drinking classes was estimated. Using the results from this final model and each individual's most likely class membership, the mean number of alcohol-dependence symptoms across classes was estimated to evaluate the clinical relevance of the results. It is important to note that these "model estimated means" are based on posterior probabilities of class membership and are estimated in the model solution.

All model parameters were estimated by the expectation-maximization algorithm using a maximum likelihood estimator with robust standard errors (MLR; Muthén and Muthén, 1998–2007). Models were estimated using automatically generated starting values with random perturbations (100 random sets of starting values with 50 optimizations in the final stage of estimation) to protect against convergence to local optima (Hipp and Bauer, 2006). For all nested model comparisons, the scaled likelihood ratio test was used to test the difference in log-likelihood between a null model in which certain parameters were fixed to equivalence across time (or treatment arms) with an alternative model in which the parameters were freely estimated across time (or treatment arms). As compared with the G^2 statistic, which has been used previously to test nested models in LTA, a scaled likelihood ratio test is necessary when comparing nested models that are estimated using MLR (Muthén and Muthén, 1998–2007). Calculations for this test are provided by Satorra (2000).

For the latent class models, the proportion of individuals expected in each class was given by the class proportion parameters (δ). Measurement parameters, ρ , represent the probability of an individual reporting a certain level of DrInC, PDD, and DDD conditional on class membership. For LTA, the transition probabilities, τ , represent the transitions between latent drinking classes. The τ parameters describe the probability of class membership at one time point, conditional on the probability of class membership from the previous time point (e.g., first-order model). See Chung et al. (2005) for an explication of the model. For LTA with covariates, the β parameters describe the distribution of latent drinking classes, conditional on alcohol dependence. The β parameters can be given as odds ratios that represent the probability of class membership at each time point relative to the odds of class membership of the specified reference class.

The relative fit of models was assessed using a multimethod approach to evaluating latent class models (Bauer and Curran, 2003; Muthén and Muthén, 2000). Models with differing numbers of classes were compared using the model log-likelihood and sample sized adjusted Bayesian Information Criterion (aBIC), which is a criterion for assessing relative model fit based on the log-likelihood and the number of parameters (Henson et al., 2007). A lower aBIC indicates a better fitting model, in comparison with models with a relatively higher aBIC. The bootstrapped likelihood ratio test (BLRT) was used to test the fit of $k-1$ classes against k classes, with a significant p value indicating that the null hypothesis of $k-1$ classes should be rejected in favor of a model with at least k classes (Lo et al., 2001; Nylund et al., 2007).

Results

Distributions of participants' responses on the three alcohol measures, as well as the means and standard deviations for the continuous measures of drinking at each time point for each treatment arm, are provided in Table 1. Both drinking quantity (as measured by DDD) and drinking frequency (as measured by PDD) were nonnormal, with standard deviations that exceeded the means at each time point. The outpatient participants endorsed fewer consequences than the aftercare participants and reported decreased consequences over time. The aftercare participants showed a decrease in DrInC scores for up to 6 months after treatment, followed by an increase in DrInC scores at 12 months.

Latent class analyses

Based on model interpretability, information criteria, and the BLRT statistic, the three-class model provided the best fit to the data. The three classes were defined as (1) *frequent heavy drinking with high consequences*, (2) *moderate infrequent drinking with low consequences*, and (3) *nondrinking with low consequences*. These three classes were sufficient to explain the heterogeneity in drinking outcomes at all time points in both outpatient and aftercare samples. Clinically, Class 3 represented those individuals who were not drinking but were experiencing some drinking-related consequences (potentially because of long-standing problems). Individuals expected to be members in Class 2 included those who drank infrequently or lightly. Individuals expected to be in Class 1 displayed heavy, frequent drinking with high drinking-related consequences. The three-class models fit significantly better than two-class models at all time points based on the BLRT, and none of the four-class models fit significantly better than the three-class models (outpatient: posttreatment BLRT = 6.22, $p = .31$; 6-month BLRT = 5.68, $p = .27$; 12-month BLRT = 7.77, $p = .08$; aftercare: posttreatment BLRT = 3.69, $p = .67$; 6-month BLRT = 4.20, $p = .50$; 12-month BLRT = 2.94, $p = .99$). The three-class models also had lower aBICs than the two-or four-class models at all time points. Additional testing of the three-class model provided support for measurement invariance with respect to time and gender across all three time points.

The item-response probabilities (p) for each category of each outcome indicator and the expected class proportions (δ) for the three latent classes at each time point for both outpatient and aftercare participants are provided in Figures 1a and 1b, respectively. These figures show how drinking outcomes defined the three classes, where the y axis represents the probability of responding positively to each item at each time point conditional on latent class membership. For example, at all time points those expected to be nondrinkers had a probability = 1 of endorsing nondrinking for PDD and DDD. Looking at the class proportions, provided in the legend, the majority of participants (57.8% of the outpatients and 75.5% of the aftercare sample) were expected to be nondrinkers immediately after treatment, but there was a decrease in the number expected to be non-drinkers at 6 months (36.7% outpatients and 52.7% aftercare). For outpatients, there was a slight increase in those expected to be nondrinkers at 12 months (40.4%).

Latent transition analysis

Effect of treatment—To test whether differences in transitions occurred between the treatment groups (CBT, MET, TSF) or treatment arms (outpatient, aftercare), the assumption of invariance of the transition probabilities across treatment was examined by estimating a series of constrained latent transition models. First, for the null model, transition probabilities were constrained to equality across both treatment groups/arms. Second, for the alternative model, the transition probabilities were allowed to vary across treatment groups/arms. The null model is nested within the alternative model, which allows for significance testing using a likelihood ratio test (Muthén and Muthén, 1998–2007) based on the scaled chi-square

difference test provided by Satorra (2000). The scaled chi-square difference test is distributed as chi-square with degrees of freedom equal to the difference in parameters between the two models. For the comparison of treatment groups, the null model with transitions held equal across treatment groups was not rejected (outpatient: scaled $\chi^2 = 35.67$, 24 df, $p = .06$; aftercare: scaled $\chi^2 = 34.68$, 24 df, $p = .07$), indicating that the transition matrices were statistically equivalent for the CBT, MET, and TSF groups. In the comparison across treatment arms, the alternative model provided a significantly better fit to the data (scaled $\chi^2 = 74.77$, 16 df, $p < .0005$), and the assumption of transition probability invariance was rejected.

The transition probabilities, shown in Table 2, indicated that most individuals were expected to remain in the same drinking class over time. There was, however, movement as indicated by transition probabilities greater than zero on the off diagonal. In the outpatient arm, the largest transition occurred from immediately after treatment to 6 months after treatment, with 22% transitioning from nondrinking to heavy drinking and 27% transitioning from nondrinking to moderate drinking. In the aftercare sample, 38% of those expected to be moderate drinkers transitioned to heavy drinking at 6 months—which was more than seven times the probability of transitioning from moderate drinking to frequent drinking in the outpatient arm.

Relationship to alcohol dependence—The final LTA was conducted with *alcohol dependence*, defined by the number of alcohol-dependence symptoms, included as a predictor of drinking-class membership and transitioning between drinking classes. As shown in Table 3, alcohol dependence was significantly related to class membership in the outpatient sample at all time points, with each additional symptom of alcohol dependence decreasing the odds of expected membership in the moderate-drinking class, as compared with both the heavy-drinking and nondrinking classes. Immediately after treatment, each additional symptom of alcohol dependence decreased the odds of expected membership in nondrinking classes, compared with heavy drinking. In the aftercare sample, each additional symptom of dependence was associated with lower odds of expected class membership in the moderate or nondrinking classes, in comparison with the heavy-drinking class, although these relationships were statistically significant only at 6 months.

The relationship between transitional probabilities and alcohol dependence is provided in the bottom of Table 3. For both the outpatient and the aftercare samples, the transition from nondrinking to heavy drinking, relative to staying classified as nondrinkers, was significantly related to alcohol dependence. Individuals who initially were expected to be in the nondrinking class after treatment were 1.2 and 1.3 times more likely to transition to heavy drinking, as compared with continued expected membership in the nondrinking class, at 6 months in the outpatient and the aftercare sample, respectively, for each additional alcohol-dependence symptom. Also, in the outpatient sample, the odds of transitioning to heavy drinking at 12 months from nondrinking at 6 months were 1.8 times greater for each additional symptom of dependence, relative to those who remained in the nondrinking class. Likewise, in both the outpatient and the aftercare samples, the odds of transitioning from heavy drinking to moderate drinking, as opposed to staying in the heavy-drinking class, was near zero at 12 months for each additional symptom of dependence. In the outpatient sample, participants with more alcohol-dependence symptoms also were more likely to get back on track after a period of heavy drinking: Participants were 1.3 times more likely to transition from heavy drinking after treatment to nondrinking at 6 months, relative to staying classified in the heavy-drinking class, for each additional symptom.

An inspection of model estimated means for the number of dependence symptoms provides a measure of the clinical significance of these findings. Individuals who were expected to maintain moderate drinking had an average of 4.63 dependence symptoms in the outpatient sample ($n = 58$) and 5.49 dependence symptoms in the aftercare sample ($n = 19$), whereas

individuals who were expected to transition to heavy drinking at 6 or 12 months (from either nondrinking or moderate drinking after treatment or 6 months, respectively) had an average of 6.31 symptoms in the outpatient sample ($n = 61$) and 7.61 symptoms in the aftercare sample ($n = 65$).

Discussion

The current study evaluated *drinking behavior*, defined by quantity, frequency, and consequences, following treatment for an alcohol-use disorder. Using data from Project MATCH, the current analyses identified *three drinking classes* in the first 12 months following treatment, defined as heavy frequent drinking with high consequences, moderate infrequent drinking with low consequences, and nondrinking with low consequences. Individuals were likely to remain in the same drinking class across time. Yet, transitioning occurred between classes, and transitioning was related to both the treatment arm and alcohol-dependence symptoms. The likelihood of transitioning did not vary by treatment assignment—which is consistent with Project MATCH (1997) findings of no treatment group differences in drinking outcomes.

Individuals in the outpatient arm were most likely to transition from nondrinking to heavy or moderate drinking initially and were likely to transition back to nondrinking by the 12-month follow-up (based on both transition probabilities and class membership across time). In the aftercare arm, participants were most likely to transition from moderate or nondrinking to heavy drinking initially but also were likely to transition back to nondrinking by the 12-month follow-up.

The finding that alcohol-dependence symptoms predicted heavy drinking and transitions to heavy drinking from either moderate or nondrinking lends support for the conceptualization of alcohol dependence as a chronic relapsing condition (McLellan, 2002). Clinically, these data suggest that individuals who are severely alcohol dependent (more than six symptoms for outpatients and seven symptoms for inpatients) are likely to have a lower probability of maintaining moderate drinking. Similarly, genetics research using the Project MATCH sample found that individuals who had a higher genetic risk for alcohol dependence reported significantly heavier drinking following treatment (Bauer et al., 2007).

The current study adds to the growing literature in support of alcohol dependence as one of several key predictors of posttreatment drinking. Several other distal and proximal risk factors have been described (Moos and Moos, 2006, 2007; Witkiewitz and Marlatt, 2004). Future research should attempt to evaluate other relapse risk and protective factors (e.g., self-efficacy, coping, social support) within a latent-variable framework to empirically test a general theoretical model of posttreatment drinking outcomes and functioning. In general, the results from the current study need to be cross-validated with a new sample. For example, are the same patterns of drinking observed among individuals in community treatment settings, as well as among individuals who do not receive formal treatment? Conducting these analyses with other populations of drinkers could help clinicians gain an understanding of the relapse process and when individuals are most likely to “fall off the wagon” or get back on.

One limitation of this study was the assessment windows (6 months separating measurement occasions). It is quite possible that periods of heavy use occurred between assessments, and the current models did not address that possibility. In addition, only the data from the first year following treatment were included. It would be interesting to examine how transitions in the first year and dependence severity relate to long-term outcomes.

One main limitation of LTA is the inability of researchers to ever know the “true” underlying distribution in the population (Bauer and Curran, 2003). The models presented in this study

provided a useful representation of the discontinuity in posttreatment drinking, but there is no way of knowing whether this representation is the best way of characterizing the lapse process. For example, nonlinear dynamic systems analysis (Hufford et al., 2003), piecewise LGMM (Colder et al., 2002), repeated measures latent class analyses (Lanza and Collins, 2006), and LGMM with regime switching (Dolan et al., 2005) may provide other means of estimating discontinuous transitions in drinking behavior. Unfortunately, all of these models, as well as LTA, are much more complex than statistical analyses with observed variables. For LTA, in particular, the contingency tables often are large and may contain sparse cells—which can lead to estimation problems.

Nonetheless, LTA has several advantages over other techniques. LTA provides a means for asking complex research questions about time- and covariate-conditional processes. The results from LTA often provide a clear and detailed summary of several interacting variables within one comprehensive model—which allows for testing systems-level hypotheses (Flaherty, 2008).

One of the primary clinical implications derived from the current study is that for individuals who received alcohol treatment the probability of returning to pretreatment patterns of frequent, uncontrolled drinking was much lower than the probability of more successful outcomes. Yet, individuals with greater alcohol-dependence symptoms were highly susceptible to heavy drinking following the initial posttreatment drinking episode and were not likely to remain in the moderate-infrequent or nondrinking class. Thus, moderate drinking goals may not be appropriate for individuals with higher levels of alcohol dependence.

References

- Auerbach KJ, Collins LM. A multidimensional developmental model of alcohol use during emerging adulthood. *J Stud Alcohol* 2006;67:917–925. [PubMed: 17061010]
- Babor TF, Cooney NL, Lauerma RJ. The drug dependence syndrome concept as a psychological theory of relapse behaviour: An empirical evaluation of alcoholic and opiate addicts. *Brit J Addict* 1987;82:393–405. [PubMed: 3472584]
- Bauer DJ, Curran PJ. Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychol Meth* 2003;8:338–363.
- Bauer LO, Covault J, Harel O, Das S, Gelernter J, Anton R, Kranzler HR. Variation in *GABRA2* Predicts Drinking Behavior in Project MATCH Subjects. *Alcsm Clin Exp Res* 2007;31:1780–1787.
- Böckenholt U. A latent Markov Model for the analysis of longitudinal data collected in continuous time: states, durations, and transitions. *Psychol Meth* 2005;10:65–83.
- Booth PG. Idiosyncratic patterns of drinking in long-term successful controlled drinkers. *Addict Res Theory* 2006;14:25–33.
- Carroll KM. Relapse prevention as a psychosocial treatment: A review of controlled clinical trials. *Exp Clin Psychopharmacol* 1996;4:46–54.
- Carroll KM, Nich C, Ball SA, McCance E, Franforter TL, Rounsaville BJ. One-year follow-up of disulfiram and psychotherapy for cocaine-alcohol users: Sustained effects of treatment. *Addiction* 2000;95:1335–1349. [PubMed: 11048353]
- Chung H, Park Y, Lanza ST. Latent transition analysis with covariates: Pubertal timing and substance use behaviors in adolescent females. *Stat Med* 2005;24:2895–2910. [PubMed: 16134129]
- Colder CR, Campbell RT, Ruel E, Richardson JL, Flay BR. A finite mixture model of growth trajectories of adolescent alcohol use: Predictors and consequences. *J Cons Clin Psychol* 2002;70:976–985.
- Connors GJ, Allen JP, Cooney NL, DiClemente CC, Tonigan JS, Anton RF. Assessment issues and strategies in alcoholism treatment matching research. *J Stud Alcohol* 1994;(12):92–100.
- Del Boca FK, Brown JM. Issues in the development of reliable measures in addictions research: Introduction to Project MATCH assessment strategies. *Psychol Addict Behav* 1996;10:67–74.

- Dolan CV, Schmittmann VD, Lubke G, Neale MC. Regime switching in the latent growth curve mixture model. *Struct Equat Model* 2005;12:94–119.
- Elal-Lawrence G, Slade PD, Dewey ME. Treatment and follow-up variables discriminating abstainers, controlled drinkers and relapsers. *J Stud Alcohol* 1987;48:39–46. [PubMed: 3029510]
- Flaherty BP. Testing the degree of cross-sectional and longitudinal dependence between two discrete dynamic processes. *Devel Psychol* 2008;44:468–480. [PubMed: 18331137]
- Goodman LA. Exploratory latent structure analysis using both identifiable and unidentifiable models. *Biometrika* 1974;61:215–231.
- Graham JW, Collins LM, Wugalter SE, Chung NK, Hansen WB. Modeling transitions in latent stage-sequential processes: A substance use prevention example. *J Cons Clin Psychol* 1991;59:48–57.
- Grant BF, Dawson DA, Stinson FS, Chou PS, Dufour MC, Pickering RP. The 12-month prevalence and trends in DSM-IV alcohol abuse and dependence: United States, 1991–1992 and 2001–2002. *Drug Alcohol Depend* 2004;74:223–234. [PubMed: 15194200]
- Guo J, Collins LM, Hill KG, Hawkins JD. Developmental pathways to alcohol abuse and dependence in young adulthood. *J Stud Alcohol* 2000;61:799–808. [PubMed: 11188485]
- Heather N, Brodie J, Wale S, Wilkinson G, Luce A, Webb E, McCarthy S. A randomized controlled trial of moderation-oriented cue exposure. *J Stud Alcohol* 2000;61:561–570. [PubMed: 10928726]
- Henson JM, Reise SP, Kim KH. Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Struct Equat Model* 2007;14:202–226.
- Hipp JR, Bauer DJ. Local solutions in the estimation of growth mixture models. *Psychol Meth* 2006;11:36–53.
- Hser YI, Shen H, Chou CP, Messer SC, Anglin MD. Analytic approaches for assessing long-term treatment effects: Examples of empirical applications and findings. *Eval Rev* 2001;25:233–262. [PubMed: 11317718]
- Hufford MR, Witkiewitz K, Shields AL, Kodya S, Caruso JC. Relapse as a nonlinear dynamic system: Application to patients with alcohol use disorders. *J Abnorm Psychol* 2003;112:219–227. [PubMed: 12784831]
- Jackson KM, O'Neill SE, Sher KJ. Characterizing alcohol dependence: Transitions during young and middle adulthood. *Exp Clin Psychopharmacol* 2006;14:228–244. [PubMed: 16756427]
- Kadden, R.; Carroll, K.; Donovan, D.; Cooney, N.; Monti, P.; Abrams, D.; Litt, M.; Hester, R. NIAAA Project MATCH Monograph Series, Vol. 3, DHHS Publication No (ADM) 92–1895. Washington: Government Printing Office; 1992. Cognitive-Behavioral Coping Skills Therapy Manual: A Clinical Research Guide for Therapists Treating Individuals with Alcohol Abuse and Dependence.
- Lanza ST, Collins LM. A mixture model of discontinuous development in heavy drinking from Ages 18 to 30: The role of college enrollment. *J Stud Alcohol* 2006;67:552–561. [PubMed: 16736075]
- Lazarsfeld, PF.; Henry, NW. Latent Structure Analysis. Boston, MA: Houghton Mifflin; 1968.
- Lo Y, Mendel NR, Rubin DB. Testing the number of components in a normal mixture. *Biometrika* 2001;88:767–778.
- McKay JR, Franklin TR, Patapis N, Lynch KG. Conceptual, methodological, and analytical issues in the study of relapse. *Clin Psychol Rev* 2006;26:109–127. [PubMed: 16371242]
- McKay JR, Lynch KG, Shepard DS, Pettinati HM. The effectiveness of telephone-based continuing care for alcohol and cocaine dependence: 24-month outcomes. *Arch Gen Psychiat* 2005;62:199–207. [PubMed: 15699297]
- McLellan AT. Have we evaluated addiction treatment correctly? Implications from a chronic care perspective. *Addiction* 2002;97:249–252. [PubMed: 11964098]
- McLellan AT, Kushner H, Metzger D, Peters R, Smith I, Grissom GP, Pettinati H, Argeriou M. The fifth edition of the Addiction Severity Index. *J Subst Abuse Treat* 1992;9:199–213. [PubMed: 1334156]
- Maisto SA, Connors GJ. Relapse in the addictive behaviors: Integration and future directions. *Clin Psychol Rev* 2006;26:229–231. [PubMed: 16360255]
- Maisto SA, Pollock NK, Cornelius JR, Lynch KG, Martin CS. Alcohol relapse as a function of relapse definition in a clinical sample of adolescents. *Addict Behav* 2003;28:449–459. [PubMed: 12628618]

- Miller WR. What is a relapse? Fifty ways to leave the wagon. *Addiction* 1996;91(Supplement):S15–S27. [PubMed: 8997778]
- Miller, WR.; C'de Baca, J. *Quantum Change: When Epiphanies and Sudden Insights Transform Ordinary Lives*. New York: Guilford Press; 2001.
- Miller WR, Del Boca FK. Measurement of drinking behavior using the Form 90 family of instruments. *J Stud Alcohol* 1994;(12):112–118.
- Miller WR, Leckman AL, Delaney HD, Tinkcom M. Long-term follow-up of behavioral self-control training. *J Stud Alcohol* 1992;53:249–261. [PubMed: 1583904]
- Miller, WR.; Tonigan, JS.; Longabaugh, R. NIAAA Project MATCH Monograph Series, Vol 4, NIH Publication No 95–3911. Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism; 1995. *The Drinker Inventory of Consequences (DrInC): An Instrument for Assessing Adverse Consequences of Alcohol Abuse (Test Manual)*.
- Miller WR, Wilbourne PL. Mesa Grande: A methodological analysis of clinical trials of treatment for alcohol use disorders. *Addiction* 2002;97:265–277. [PubMed: 11964100]
- Miller, WR.; Zweben, A.; DiClemente, CC.; Rychtarik, RG. NIAAA Project MATCH Monograph Series, Vol 2, NIH Publication No (ADM) 92–1894. Washington: Government Printing Office; 1992. *Motivational Enhancement Therapy Manual: A Clinical Research Guide for Therapists Treating Individuals with Alcohol Abuse and Dependence*.
- Moos RH, Moos BS. Sixteen-year changes and stable remission among treated and untreated individuals with alcohol use disorders. *Drug Alcohol Depend* 2005;60:337–347. [PubMed: 15946805]
- Moos RH, Moos BS. Rates and predictors of relapse after natural and treated remission from alcohol use disorders. *Addiction* 2006;101:212–222. [PubMed: 16445550]
- Moos RH, Moos BS. Protective resources and long-term recovery from alcohol use disorders. *Drug Alcohol Depend* 2007;86:46–54. [PubMed: 16769181]
- Muthén B, Muthén LK. Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcsm Clin Exp Res* 2000;24:882–891.
- Muthén, LK.; Muthén, BO. *Mplus User's Guide, Version 5*. Los Angeles, CA: Muthén and Muthén; 1998–2007.
- National Institute on Alcohol Abuse and Alcoholism. NIAAA Newsletter, winter, No 3, p 3, NIH Publication No 04–5346. Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism; 2004. *NIAAA Council Approves Definition of Binge Drinking*.
- Nowinski, J.; Baker, S.; Carroll, K. NIAAA Project MATCH Monograph Series, Vol 1, NIH Publication No (ADM) 92–1893. Washington: Government Printing Office; 1992. *Twelve Step Facilitation Therapy Manual: A Clinical Research Guide for Therapists Treating Individuals with Alcohol Abuse and Dependence*.
- Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling. A Monte Carlo simulation study. *Struct Equat Model* 2007;14:535–569.
- Project MATCH Research Group. Rationale and methods for a multisite clinical trial matching patients to alcoholism treatment. *Alcsm Clin Exp Res* 1993;17:1130–1145.
- Project MATCH Research Group. Matching alcoholism treatments to client heterogeneity: Project MATCH posttreatment drinking outcomes. *J Stud Alcohol* 1997;58:7–29. [PubMed: 8979210]
- Russell M, Light JM, Gruenewald PJ. Alcohol consumption and problems: The relevance of drinking patterns. *Alcsm Clin Exp Res* 2004;28:921–930.
- Satorra, A. Scaled and adjusted restricted tests in multi-sample analysis of moment structures. In: Heijmans, RDH.; Pollock, DSG.; Satorra, A., editors. *Innovations in Multivariate Statistical Analysis: A Festschrift for Heinz Neudecker*. Norwell, MA: Kluwer Academic; 2000. p. 233–247.
- Sobell MB, Sobell LC. Controlled drinking after 25 years: How important was the debate? *Addiction* 1995;90:1149–1152. [PubMed: 7580815]
- Spitzer, RL.; Williams, JB., editors. *Structured Clinical Interview for DSM-III-R, Patient Version*. New York: New York State Psychiatric Institute; 1985.
- Stinson, FS.; Yi, H-Y.; Grant, BF.; Chou, P.; Dawson, DA.; Pickering, R. *Alcohol Epidemiologic Data Reference Manual*, NIH Publication No 99–3519. Vol. 1. Vol. 6. Washington: Government Printing Office; 1998. *Drinking in the United States: Main Findings From the 1992 National Longitudinal Alcohol Epidemiologic Survey (NLAES)*, U.S.

- Stout RL. What is a drinking episode? *J Stud Alcohol* 2000;61:455–461. [PubMed: 10807219]
- Stout RL. Methodological and statistical considerations in measuring alcohol treatment effects. *Alcsm Clin Exp Res* 2003;27:1686–1691.
- Stout RL. Advancing the analysis of treatment process. *Addiction* 2007;103:1539–1545. [PubMed: 17610542]
- Sutton SR. Interpreting relapse curves. *J Cons Clin Psychol* 1979;47:96–98.
- Velicer WF, Martin RA, Collins LM. Latent transition analysis for longitudinal data. *Addiction* 1996;91 (Supplement):S197–S209. [PubMed: 8997793]
- Windle M, Mun EY, Windle RC. Adolescent-to-young adulthood heavy drinking trajectories and their prospective predictors. *J Stud Alcohol* 2005;66:313–322. [PubMed: 16047520]
- Witkiewitz K, Marlatt GA. Relapse prevention for alcohol and drug problems: That was Zen, this is Tao. *Amer Psychol* 2004;59:224–235. [PubMed: 15149263]
- Witkiewitz K, Masyn K. Drinking trajectories following an initial lapse. *Psychol Addict Behav.* in press
- Witkiewitz K, van der Maas HLJ, Hufford MR, Marlatt GA. Nonnormality and divergence in posttreatment alcohol use: Reexamining the Project MATCH data “another way”. *J Abnorm Psychol* 2007;116:378–394. [PubMed: 17516769]
- World Health Organization. *The World Health Report 2002: Reducing Risks, Promoting Healthy Life.* Geneva, Switzerland: World Health Organization; 2002.
- Wu J, Witkiewitz K. Network support for drinking: An application of multiple groups growth mixture modeling to examine client-treatment matching. *J Stud Alcohol Drugs* 2008;69:21–29. [PubMed: 18080061]

LCA Results - Three Class Model Outpatient
Immediately After Treatment

LCA Results - Three Class Model Outpatient
6 Months After Treatment

LCA Results - Three Class Model Outpatient
12 Months After Treatment

Figure 1.

Figure 1a. Conditional item probability plots for the three-class models for immediately after treatment and at 6 and 12 months after treatment in the outpatient sample. Class proportions are presented in the legend. LCA = latent class analysis; DrInC = Drinker Inventory of Consequences; DDD = drinks per drinking day.

Figure 1b. Conditional item probability plots for the three-class models for immediately after treatment and at 6 and 12 months after treatment in the aftercare sample. Class proportions are presented in the legend. LCA = latent class analysis; DrInC = Drinker Inventory of Consequences; DDD = drinks per drinking day.

Table 1
Observed item response frequencies and associated means and standard deviations based on the continuous measures of drinking consequences, frequency, and quantity, by treatment arm

Variable/treatment arm	Posttreatment Mean (SD) or <i>n</i> (%)	6-month follow-up Mean (SD) or <i>n</i> (%)	12-month follow-up Mean (SD) or <i>n</i> (%)
Outpatient			
DrInC total, mean (SD)	32.85 (25.14)	28.07 (23.12)	27.72 (22.28)
Low (DrInC < 10)	91 (19.0%)	114 (27.9%)	111 (29.1%)
Medium (DrInC = 10–39)	240 (50.2%)	181 (44.4%)	163 (42.8%)
High (DrInC ≥ 40)	147 (30.8%)	113 (27.7%)	107 (28.1%)
Quantity, mean (SD)	4.06 (6.96)	5.56 (6.43)	5.38 (6.68)
Nondrinking (DDD = 0)	385 (57.6%)	238 (36.7%)	253 (40.4%)
Moderate drinking (DDD < 5 for men, DDD < 4 for women)	98 (14.7%)	126 (19.4%)	120 (19.2%)
Heavy drinking (DDD ≥ 5 for men, DDD ≥ 4 for women)	185 (27.7%)	285 (43.9%)	253 (40.4%)
Frequency, mean (SD)	0.20 (0.31)	0.27 (0.34)	0.27 (0.35)
Non-drinking (PDD = 0)	385 (57.6%)	238 (36.7%)	253 (40.4%)
Infrequent drinking (PDD < 50%)	178 (26.6%)	258 (39.8%)	224 (35.8%)
Frequent drinking (PDD ≥ 50%)	105 (15.7%)	153 (23.6%)	149 (23.8%)
Aftercare			
DrInC total, mean (SD)	40.34 (28.97)	28.69 (27.25)	39.66 (26.71)
Low (DrInC < 10)	44 (16.0%)	52 (18.8%)	56 (18.4%)
Medium (DrInC = 10–39)	117 (42.5%)	96 (34.7%)	102 (33.6%)
High (DrInC ≥ 40)	114 (41.5%)	129 (46.6%)	146 (48.0%)
Quantity, mean (SD)	2.96 (7.14)	5.83 (9.22)	5.89 (9.42)
Nondrinking (DDD = 0)	439 (75.4%)	303 (52.9%)	294 (52.6%)
Moderate drinking (DDD < 5 for men, DDD < 4 for women)	40 (6.9%)	57 (9.9%)	62 (11.1%)
Heavy drinking (DDD ≥ 5 for men, DDD ≥ 4 for women)	103 (17.7%)	213 (37.2%)	203 (36.3%)
Frequency, mean (SD)	0.14 (0.30)	0.21 (0.32)	0.23 (0.35)
Nondrinking (PDD = 0)	439 (75.4%)	303 (52.9%)	294 (52.6%)
Infrequent drinking (PDD < 50%)	69 (11.9%)	166 (29.0%)	153 (27.4%)
Frequent drinking (PDD ≥ 50%)	74 (12.7%)	104 (18.2%)	112 (20.0%)

Notes: DrInC = Drinker Inventory of Consequences; DDD = drinks per drinking day; PDD = percentage of drinking days.

Table 2
Transition probabilities (τ) for time heterogeneous latent transition analysis

	Outpatient						Aftercare					
	Posttreatment-Month 6			Month 6-Month 12			Posttreatment-Month 6			Month 6-Month 12		
	1. Heavy	2. Mod.	3. Non.	1. Heavy	2. Mod.	3. Non.	1. Heavy	2. Mod.	3. Non.	1. Heavy	2. Mod.	3. Non.
1. Heavy frequent	.766	.042	.192	.791	.044	.165	.806	.000	.194	.741	.000	.259
Moderate infrequent	.050	.832	.118	.026	.777	.197	.379	.521	.100	.104	.714	.182
Nondrinking	.221	.269	.509	.087	.115	.798	.231	.124	.645	.147	.068	.784

Notes: Heavy = heavy frequent drinking class; mod. = moderate infrequent drinking class; non. = nondrinking class.

Table 3

Odds ratios (OR) for latent transition analysis with class membership and transitions regressed on the number of current alcohol dependence symptoms

Class membership	Outpatient: Alcohol dependence symptoms				Aftercare: Alcohol dependence symptoms			
	Posttreatment OR (95% CI)	Month 6OR (95% CI)	Month 12OR (95% CI)		Posttreatment OR (95% CI)	Month 6 OR (95% CI)	Month 12OR (95% CI)	
Non. vs heavy ^a	0.87 (0.78–0.96) *	1.01 (0.90–1.13)	0.87 (0.93–1.02)		0.94 (0.79–1.11)	0.81 (0.70–0.94) *	0.97 (0.86–1.10)	
Mod. vs heavy ^a	0.64 (0.54–0.77) *	0.78 (0.65–0.92) *	0.70 (0.54–0.91) *		0.82 (0.60–1.13)	0.71 (0.59–0.85) *	0.85 (0.69–1.05)	
Mod. vs non. ^a	0.74 (0.63–0.87) *	0.77 (0.66–0.88) *	0.81 (0.68–0.96) *		0.88 (0.72–1.08)	0.87 (0.75–1.01)	0.88 (0.73–1.06)	
	Posttreatment-Month 6 OR (95% CI)		Month 6-Month 12 OR (95% CI)		Posttreatment-Month 6 OR (95% CI)		Month 6-Month 12 OR (95% CI)	
Non. to mod. vs non. ^a	0.79 (0.68–0.91) *		0.85 (0.65–1.10)		0.89 (0.76–1.04)		0.86 (0.69–1.07)	
Non. to heavy vs non. ^a	1.16 (1.01–1.35) *		1.79 (1.20–2.66) *		1.32 (1.14–1.53) *		1.14 (0.96–1.35)	
Mod. to non. vs mod. ^a	1.37 (0.99–1.90)		1.17 (0.94–1.45)		1.14 (0.80–1.64)		1.30 (1.07–1.57) *	
Mod. to heavy vs mod. ^a	0.60 (0.33–1.11)		1.26 (0.90–1.77)		0.12 (0.09–0.15) *		2.56 (0.66–9.98)	
Heavy to non. vs heavy ^a	1.34 (1.06–1.69) *		1.09 (0.88–1.31)		1.10 (0.81–1.48)		1.11 (0.84–1.46)	
Heavy to mod. vs heavy ^a	0.79 (0.48–1.29)		0.00 (0.00–0.003) *		0.25 (0.13–0.46) *		0.02 (0.00–0.10) *	

Notes: Heavy = heavy frequent drinking class; mod. = moderate infrequent drinking class; non. = nondrinking class.

^aReference class in multinomial logistic regression, $p < .05$.

* $p < .05$.