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A LONGITUDINAL APPROACH TO UNDERSTANDING INDIVIDUAL DIFFERENCES AFFECTING THE DRINKING BEHAVIOR CHANGE PROCESS

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**A LONGITUDINAL APPROACH TO UNDERSTANDING INDIVIDUAL
DIFFERENCES AFFECTING THE DRINKING BEHAVIOR CHANGE PROCESS**

**By
Mariam Dum**

A Dissertation Presented to the School of Psychology
of Nova Southeastern University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy

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DEDICATION

For my grandparents, Moshe and Rosa Dum, and Jose and Hilda Levy, for their important legacy of humility and education that is summarized in the following quote by Moshe ben Maimon: “Teach thy tongue to say I do not know and thou shalt progress.”

A special remark: I will never forget the proud expression on my grandfather’s face, el abuelo Dum, when he saw my first senior author publication with his last name on it.

In addition, I want to dedicate my work to my daughter, Gabriela and hopefully, future children, as an example of what I learned from my grandparents and parents about the importance of hard work, inspiration, and dedication to the wellbeing of our society.

ABSTRACT

Most studies examining predictors of treatment outcomes among problem drinkers have used a traditional statistical approach that examines group outcomes (e.g. analysis of variance, multiple regression analysis). Contrary to traditional methods, a person-centered approach identifies commonalities among clusters of individuals and provides the opportunity to examine the relationship between multiple individual differences and outcomes in a longitudinal manner. Specifically, the person-centered approach makes it possible to cluster individuals into subgroups based on their change patterns, and to examine the relationship between those subgroups and other variables of interest (e.g., drinking problem severity). This approach allows the inclusion of a relatively large number of variables to test complex hypotheses. The present study is a secondary data analysis of early (first three-month) Timeline Followback (TLFB) post-treatment drinking data from 200 problem drinkers who completed a short outpatient intervention. Using a growth mixture modeling (GMM) analysis, the goal was to identify different outcome drinking trajectories and examine the relationship between problem severity levels, treatment modality (i.e. individual versus group format), and goal choice (i.e. low-risk drinking versus abstinence) to those trajectories. Results demonstrated the existence of different outcome subgroups among problem drinkers. In addition, problem severity level was associated with outcomes and class membership. Observed significant differences in the relationships between predictor variables and specific outcome subgroups, and evidence of different drinking fluctuation patterns in the outcomes suggest that using a person-centered approach adds value beyond traditional statistical

outcome analyses. The person-centered approach can facilitate the identification of relevant variables for patient-treatment matching hypotheses for problem drinkers.

CHAPTER 1:

Statement of the Problem

Individuals with alcohol use disorders (AUD) can differ on many dimensions including premorbid level of drinking, developmental trajectories, demographic characteristics, manifestation of symptoms, level of functional impairment, and types of high-risk drinking situations (i.e. Annis & Graham, 1995; Bucholz, Heath, Reich, Hesselbrock, & et al., 1996; Fuzhong, Duncan, Duncan, & Hops, 2001; Monga et al., 2007; Rindskopf, 2006; Schulenberg, O'Malley, Bachman, Wadsworth, & Johnston, 1996; Zucker, 1994). Taking account of these differences, studies have tried to identify client characteristics that predict treatment outcomes using a variety of therapeutic approaches, as no single treatment has proven effective with all alcohol abusers (Donovan et al., 1994; Project Match Research Group, 1993).

Problem drinkers are a not severely dependent subgroup among individuals with AUDs (Sobell & Sobell, 1993). Demographic variables, severity levels, number of alcohol-related consequences, positive outcomes of low-risk drinking, and a good success rate for brief interventions have been found to differentiate problem drinkers from more severely dependent alcohol abusers (Graham, Annis, Brett, & Venesoen, 1996; Marques & Formigoni, 2001; Sobell, Sobell, & Agrawal, in press). Problem drinkers have been found to respond positively to Motivational Interviewing (MI) and to Cognitive-Behavioral Treatment (CBT) conducted in either an individual or group format (e.g. Agosti, 1995; Graber & Miller, 1988; Graham et al., 1996; Heather et al., 2000; Marques & Formigoni, 2001; Project Match Research Group, 1997; Sanchez-Craig, Annis, Bornet, & MacDonald, 1984; Sobell et al., in press; Weiss, Jaffee, deMenil, & Cogley, 2004).

However, while the majority of problem drinkers demonstrate improvement after treatment, some individuals do not respond well to treatment. Therefore, examining client-treatment interactions might provide valuable information for creating client-treatment hypotheses specific to problem drinkers.

In this study, data from a randomized controlled clinical trial that found no outcome differences between problem drinkers who were assigned to individual or group treatment using the Guided Self Change (GSC) model of treatment (Sobell et al., in press) will be used to examine types of drinking patterns shown by clients shortly after treatment, and the relationship of pretreatment characteristics to these patterns. The GSC intervention consists of a brief, outpatient treatment using both motivational interviewing and cognitive-behavioral techniques to aid in changing an individual's drinking behavior. The GSC model has been extensively evaluated and is an empirically-supported, cost-effective treatment for problem drinkers (Sobell & Sobell, 2005).

Although several studies have examined the relationship of predictors to treatment outcomes among problem drinkers over the past thirty years (e.g. Adamson & Sellman, 2001; Blume, Marlatt, & Schmaling, 2000; Booth, Dale, & Ansari, 1984; Booth, Dale, Slade, & Dewey, 1992; Brown, Carrello, Vik, & Porter, 1998; Chang, McNamara, Orav, & Wilkins-Haug, 2006; Cronkite & Moos, 1984; Donovan, Kivlahan, Kadden, & Hill, 2001; Edwards, Brown, Oppenheimer, Sheehan, Taylor, & Duckitt, 1988; Graber & Miller, 1988), the relationship of pre-treatment drinking patterns to treatment outcomes has been relatively unstudied. To some extent, such inquiries have been limited by the use of traditional group-centered statistical methods (e.g. analysis of variance, regression analysis). A person-centered approach is a new technique that examines individual

differences by using cluster, latent class, and latent transition analyses (Muthén & Muthén, 2000). Due to the observed multidimensional dysfunction in alcohol abusers, it cannot be expected that a single variable would account for a large proportion of the variance in outcomes (Project Match Research Group, 1998). Therefore, a realistic research objective would be to find subgroups defined by multiple variables and examine their relationship to treatment outcomes. An important advantage of a person-centered approach is in the analysis of a bimodal distribution (Witkiewitz, van der Maas, Hufford, & Marlatt, 2007). For most treatment studies in the addiction field, the analysis of outcome data involves groups of responders and non-responders, forming a bimodal distribution. Since group approaches involve the assumption of normality, this type of distribution is not the most optimal for traditional statistical methods (e.g. analysis of variance, regression analysis).

Using traditional statistical methods, researchers have largely failed to find significant results for client-treatment interactions in alcohol studies (Project Match Research Group, 1993, 1997). With regard to problem drinkers, many potentially important matching variables have been relatively unexamined. Regarding treatment format (individual versus group modality), very few controlled studies have compared efficacy levels of treatment formats in problem drinkers (Weiss et al., 2004). These studies that have been conducted have found no significant differences between formats. Another important variable in the problem drinker literature is goal-choice, as many problem drinkers will seek to reduce rather than stop their drinking (Sobell & Sobell, 1995). Such factors can be included in a person-centered analytic data approach.

Surprisingly, a limited number of studies have examined the nature of individuals' specific pretreatment drinking patterns as predictors of outcomes, even though consumption is the cardinal symptom of alcohol use disorders. Sobell, Sobell, and Gavin (1995) argued for examining alcohol variables other than summary measures (e.g. percentage of drinking days) since this type of measurement does not consider drinking pattern fluctuations. Information gathered by studying such relationships may suggest client-treatment matching hypotheses for future studies (Project Match Research Group, 1993; Sobell & Sobell, 1999). Some studies have used percentage of drinking days and the number of drinks per drinking days to reliably classify individuals based on their drinking patterns after treatment (Witkiewitz, 2008; Witkiewitz & Masyn, 2008; Witkiewitz et al., 2007).

The current study uses person-centered analyses to classify a set of outcome trajectories based on drinking patterns after treatment and to examine the relationship of alcohol-related consequences, pretreatment drinking patterns, goal choice and treatment format to those outcomes. It should be cautioned that the post-treatment interval analyzed was limited to 90 days for these analyses, and thus any clusters identified should be considered as not necessarily representing stable outcomes. It is hypothesized that meaningful classes will be obtained from the post-treatment drinking trajectories, and that alcohol-related consequences, pre-morbid drinking patterns, goal choice, and treatment modality will be associated with treatment outcomes.

CHAPTER II:

Review of the Literature

Overview of Person-Centered Statistical Methods

Over the past 20 years, some researchers in the alcohol field have begun using advanced longitudinal statistical techniques to analyze trajectory patterns in the drinking of alcohol abusers (i.e. Bucholz et al., 1996; Fuzhong et al., 2001; Monga et al., 2007; Rindskopf, 2006; Zucker, 1994). New methodologies have been developed to examine the dynamic relationship between variables predicting outcomes as a function of time and covariates (Witkiewitz & Masyn, 2008). These techniques allow for the creation of a number of classes based on both cross-sectional and longitudinal information. Therefore, the use of a person-centered approach for data analysis can highlight differences within and between effects of important variables in identified outcome subgroups.

Latent Class Analysis and Latent Profile Analysis

The objective of latent class (LCA) and latent profile analyses (LPA) is to discover a small number of unobserved classes that best articulate the association between categorical and continuously observed variables (McCutcheon, 1987; Muthén & Muthén, 2000). Since a latent variable accounts for the relationship between observed variables, both models can be compared to factor analysis. However, in LCA and LPA, the residuals are assumed to be uncorrelated and the assumption of independence of the observed variables is more likely to hold true. Latent class analysis is used when the observed variables are categorical, whereas LPA is used when the variables are continuous. The aim of the LCA and LPA is to find clusters of individuals who share similarities among a number of observed, concentrated variables. Both models assist in

the detection of a set of variables that describe the probability of inclusion of any individual into an unobserved category. For example, the observed variables can be presence or absence of a number of alcohol-related consequences, and the latent (unobserved) classes may describe different patterns of these consequences.

In LCA and LPA, the parameters of the model are the probabilities of membership in categories and of satisfying class membership criteria. Individuals are assigned to the different latent classes based on their posterior probabilities for class membership, according to the selected standards. The probability of a particular individual belonging to a class is determined solely by the data and that the necessary number of classes results in conditional independence among the observed outcomes (Muthén, 2002). Dependence among the variables exists within each class as LCA and LPA allow the grouping of individuals into different clusters according to the observed indicators included in the analysis. Then, the process estimates the probability that a particular individual is a member of a specific class. In finding the appropriate number of classes, the analysis adds classes stepwise until the model has the best fit to the data (Muthén & Muthén, 2000).

Figure 2.1 describes LCA. Figure 2.1a shows a corresponding model diagram for Figure 2.1b. The square boxes in Figure 2.1a represent the indicators, which are the observed variables and the circle represents the categorical latent variable C with four categories. The LCA has the following two key elements: (a) the influence of C to the indicators and (b) the prevalence for the four classes. Figure 2.1b displays the probability of individuals in that class endorsing the indicator. The graph shows four latent classes that are homogeneous, yet different across classes according to the four indicators. That

is, individuals across classes differ in their probability of endorsing the different indicators.

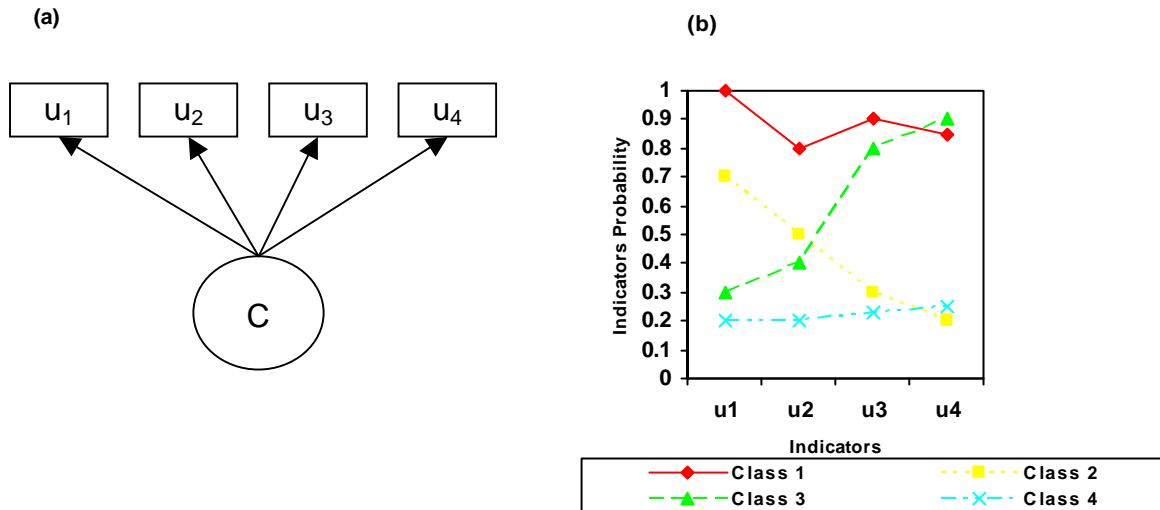


Figure 2.1

Path Diagram and Graph for a Latent class analysis (LCA)

Latent Class Growth Analysis

Latent class growth analysis (LCGA) is a group-based trajectory model. LCGA uses a single outcome variable measured across several time points to describe a number of latent class models, where there is correspondence to different growth curve shapes for the outcome variable (Muthén & Muthén, 2000). The goal is to find the probability of class membership, as well as the different growth curve shapes. Individuals belong to different classes characterized by different trajectory types, where one can exhibit two classes, in which the shapes of change differ among the classes. For example, one may have a linear shape while the other may have a quadratic shape. While the groups will differ in their trajectory, the model assumes no further variation within the group (Kreuter

& Muthén, Draft). As seen in Figure 2.2a, this suggests that the categories are completely independent of one another; therefore, no relationship is assumed among the categories (Muthén, 2001a). Figure 2.3a shows the path diagram for a LCGA with quadratic growth function, where the growth parameters, the intercept factor (β_0), the linear slope factor (β_1), and the quadratic slope factor (β_2) vary across categories (Kreuter & Muthén, Draft). The observed variables that account for the time points for the outcome variable are represented by u_1 - u_4 . Notice that there are no residual errors in the growth parameters, which suggest that individuals within each C class are treated as identical in relation to their trajectory. Variations are seen across each class with respect to the set of intercept and slopes among classes. Figure 2.3b represents how the classes differ among the three growth parameters (intercept and slope). Differences across the classes within the parameters result in different trajectories for the outcome variable.

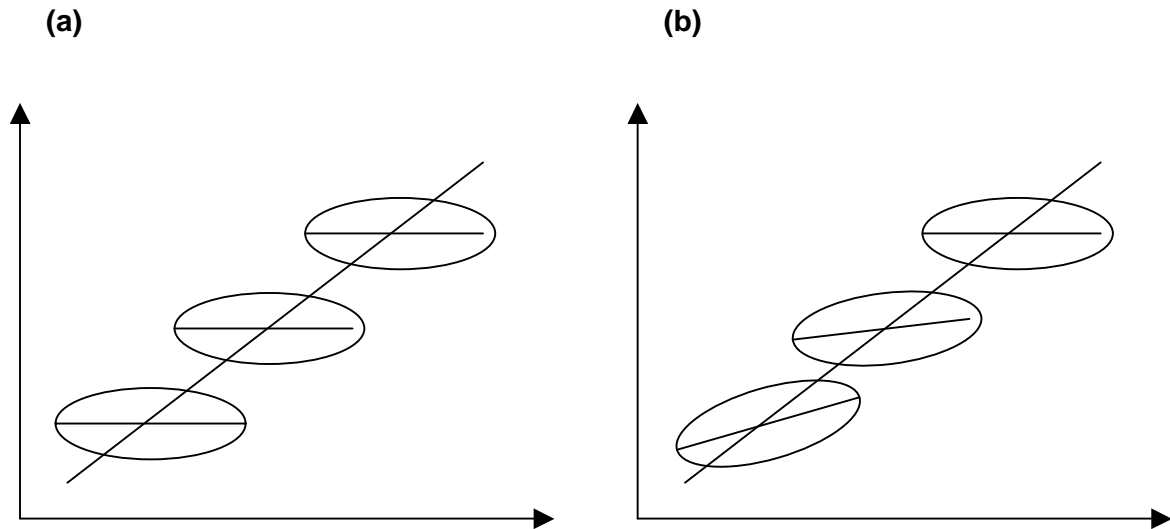


Figure 2.2

Differences among the Latent Class Growth Model (LCGA) and General Mixture Model (GMM) Categories

Note: As Figure 2.2a represents, the LCAG categories are independent of each other. The actual variation in the growth factors is represented by discrete points, therefore, no distribution is assumed. In contrast, the GMM allows the categories to have some variation or random effects within the classes. Thus, categories in the GMM are allowed to correlate.

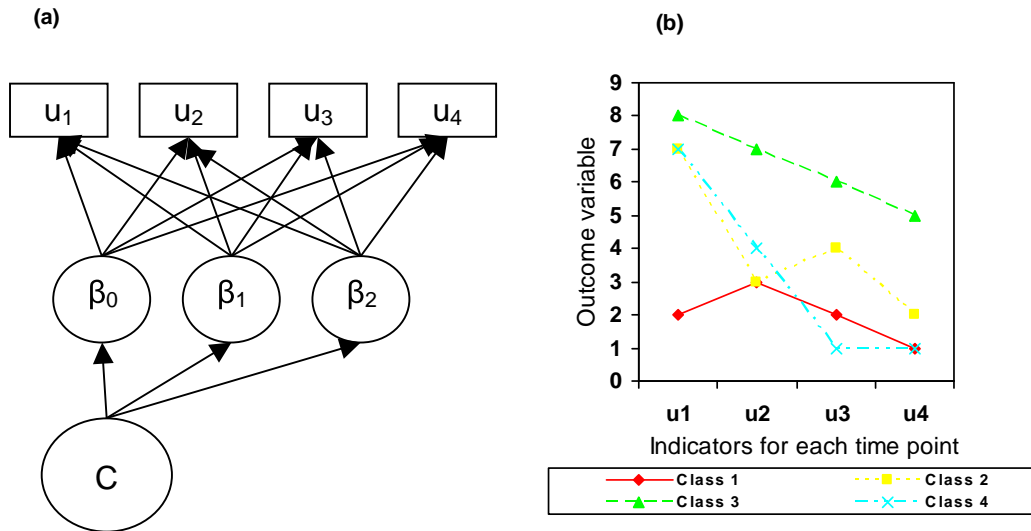


Figure 2.3

Path Diagram and Graph for a Latent Class Growth Model (LCGA)

Growth Mixture Modeling

Growth mixture modeling (GMM) is employed when the research provides a theoretical basis for how different antecedents and consequences affect individuals' outcomes. The model analyzes longitudinal data by relating an observed outcome variable to time or time-related variables (e.g., age) and capturing individual variations on a number of continuous latent variables (Muthén & Muthén, 2000). Growth mixture modeling is based on the conventional growth curve modeling technique where a growth curve is estimated for the population and individual differences are obtained through the variability of the growth factors (intercept and the different slopes types). Individual variations on the outcome variable at the different time points are captured by random coefficients or random effects, which are the continuous latent variables or growth factors (intercept and slopes) that vary across individuals. Random effects capture the individual

differences over time in an heterogeneous sample by using the Laird and Ware (1982) type of model. These differences can be observed by different start rates (intercept) and growth rates (slope). Therefore, the random coefficients let the intercept and slope vary across individuals.

In the conventional growth model, it is assumed that the covariates have the same influence on the growth factors. However, this assumption may not apply to alcohol and substance abuse research (Li, Duncan, & Hops, 2001) since this group usually represents a heterogeneous population where the covariates affect the various subpopulations in different manners. Therefore, GMM may be a more realistic statistical approach to data analysis because it allows the covariates to influence the growth factors in different ways.

Growth Mixture Modeling combines features of conventional growth modeling and LCGA (Muthén & Muthén, 2000). While conventional growth modeling estimates the growth factor variances for a homogeneous population, GMM considers a heterogeneous population by capturing a mixture of distinct subgroups, which have been defined by a prototypical growth curve (Wiesner & Windle, 2004). Like in LCGA, GMM projects a mean curve for each class. However, unlike LCGA, the individuals' variations are captured by the latent class, which is represented by random effects and are set to be correlated in GMM. This approach captures the variation of the mean growth curves of each class, as well as the individual variation of the growth curves by estimating the growth factor variances (Muthén, 2001b; Muthén & Muthén, 2000). Figure 2.4a shows a path diagram for a GMM with a quadratic growth function (Kreuter & Muthén, Draft). The growth parameters, the intercept factor (β_0), the linear slope factor (β_1), and the quadratic slope factor (β_2), vary by classes C with random effects on the intercept, linear

slope, and quadratic slope within classes, which are represented by the small arrowheads. In the GMM model, all the growth factor variances are not set at zero, but can vary within class. If the growth factors are set to zero, a GMM model provides the same results as an LCGA. With GMM, researchers are able to examine how individuals with certain characteristics respond differently to the effects of a specific treatment modality by analyzing the latent trajectory class for the repeated measures as in LCGA. However, with GMM a more parsimonious model is obtained yielding fewer categories due to the assumption that within the same class individual variability exists (see Figure 2.2). These class disparities or residual errors are assumed to be normally distributed. As in the LCGA, Figure 2.4b represents how the classes differ among the three growth parameters (intercept and slope). Distinctions across the classes within the parameters result in different trajectories for the outcome variable.

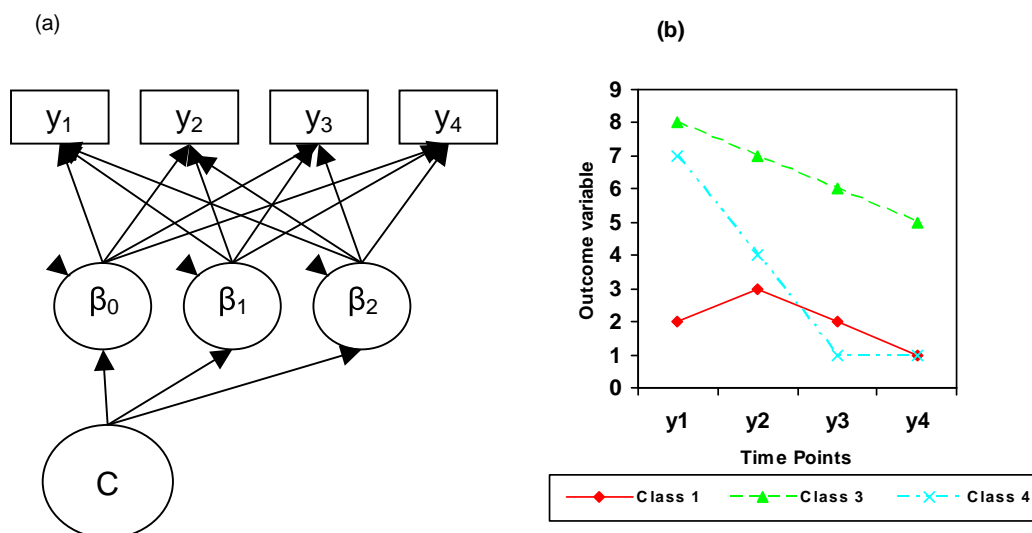


Figure 2. 4

Path Diagram and Graph for a Growth Mixture Model (GMM)

Growth Mixture Models allow researchers to understand how certain trait-like characteristics affect individuals' change across time by categorizing them according to similar characteristics. For example, there are a number of alcohol-related triggers that affect alcohol abusers' abilities to resist urges to drink. Generally, individuals differ in what stimuli prompt their drinking and to what extent this happens. It may be the case that the type of triggers manifested by each individual significantly affects their treatment outcomes and how they change over time.

General Growth Mixture Modeling

General growth mixture modeling (GGMM) involves models that incorporate the GMM covariates, distal outcomes or sequential processes, among other factors (Muthén & Muthén, 2000). Since this method involves the characteristics of all the prior models, Table 2.1 summarizes the similarities and differences (Muthén, 2001a). In GGMM, researchers potentially include categorical as well as continuous observed variables to define the latent class. As with GMM, class variances are allowed. One can estimate growth curve shapes from longitudinal data, where the different class growth curve shapes are not only influenced by the variables used to predict the classes, but also by other relevant variables.

Table 2.1

Summary of Techniques Using Latent Classes

<i>Class</i>	<i>Outcome/Indicator</i>		<i>Number of</i>
	<i>Scale</i>	<i>Time Points</i>	<i>Within Class Variation</i>
LCA	Categorical (u)	Single	No
LPA	Continuous (y)	Single	No
LCGA	Categorical (u)	Multiple	No
GMM	Continuous (y)	Multiple	Yes
GGMM	Categorical (u)/ Continuous (y)	Multiple	Yes

Note: LCA – latent class analysis, LPA – latent profile analysis, LCGA – latent class growth analysis, GMM – growth mixture modeling, GGMM – general growth mixture modeling.

General Growth Mixture Modeling has different beneficial applications (Muthén, 2002). Allowing for heterogeneity analysis in the population and assumption of individual growth curves, this model identifies a mixture of subpopulations with varying fixed effects. Group level characteristics, random effects, and individual variation are estimated (Fuzhong et al., 2001). Growth General Mixture Models also allow for the influence of time-variant and time-invariant covariates in growth trajectory analyses. The model examines the impact of covariates on the probability of group membership (Muthén, 2002). For instance, an investigator may be interested in examining how latent classes found before treatment can relate to outcome trajectories of classes based on treatment modality. Another type of analysis consists of using the latent trajectory classes as predictors of distal outcomes in the form of binary u variables, such as exploring the

predictive power of drinking pattern class trajectories on a distal outcome like alcohol dependence. In a third application, covariates can be used as either time-variant or time-invariant (Muthén, 2002). While the former covariates have an effect on the outcomes, the latter covariates have an effect on the classes. Figure 2.5a represents a GGMM model that includes a covariate (x), a latent class variable (c), and repeated continuous outcomes (y). Here, the covariate x influences c and has a direct effect on the growth factors β_0 , β_1 , and β_2 . In the prediction of the latent class variable by the covariate, the probability of inclusion in either class changes as a result of the covariate. As illustrated in Figure 2.5b, the odds of inclusion in a class are different based on gender. The covariate may also have an effect on the growth factors (intercept and shape of the slope) that can change as a result of the covariate. As shown in Figure 2.5b, for instance, the intercept and slopes for each of the classes change when males and females are separated.

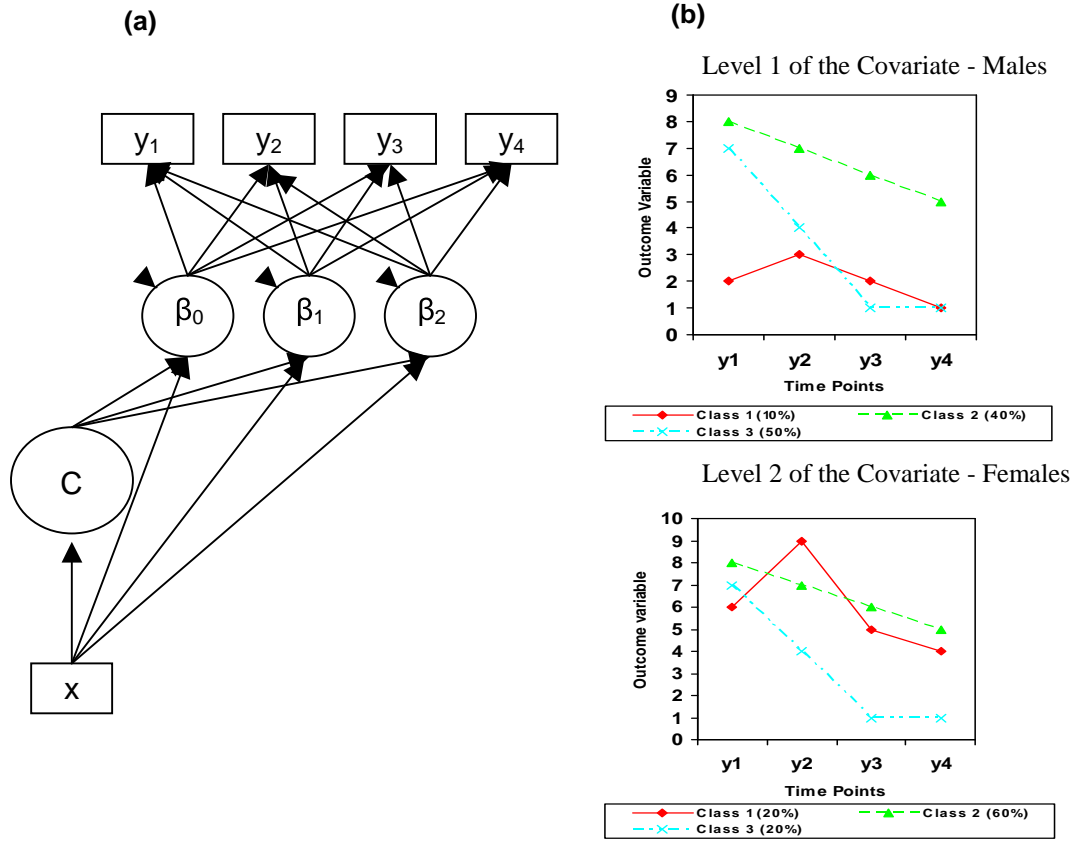


Figure 2.5

Path Diagram and Graph for a General Growth Mixture Model (GGMM) with a Covariate

A different GGMM model is the sequential GMM, where more than one growth mixture model is estimated and the latent classes of the second model are related to the latent classes of the first process (see Figure 2.6). For each process, three growth factors are used corresponding to the intercept (β_0), linear (β_1) and quadratic slope (β_2). Each of the growth factors is influenced by a latent class variable specific to the process, so that the means of the growth factors change over classes (Muthén, 2001a). It is a type of latent transition analysis (LTA), which is particularly suited to modeling change in group

membership over time (Muthén & Muthén, 1998-2007). In these models, transition probabilities describe the prospect of transitioning from a given class to another in the next process. For example, a researcher may want to determine whether a population of individuals, who were classified in two classes, heavy drinkers and moderate drinkers, tend to use more or less drugs according to another GMM (see Figure 2.6). The aim is to understand how members of one class transition to the next class.

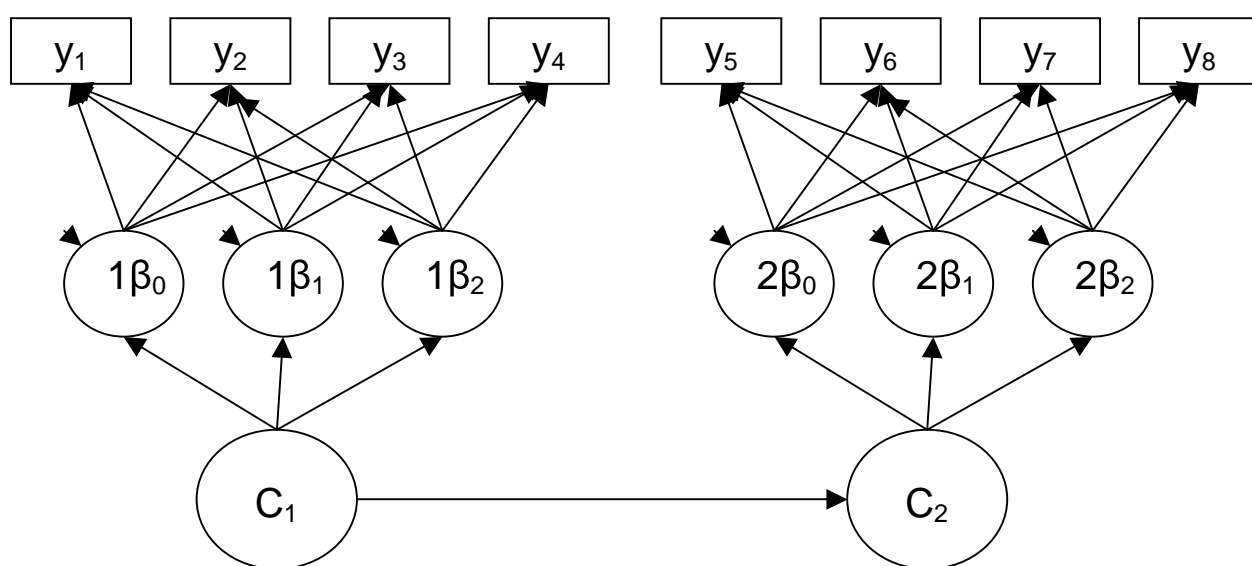


Figure 2.6

A Sequential Process GMM for Continuous Outcomes with Two Categorical Latent Variables

Growth General Mixture Models provide researchers with the opportunity to analyze not only the effect that classes have on change patterns, but also how certain time-invariant variables affect the trajectories of the classes. Given the heterogeneous characteristic of alcohol abusers, adding covariates to the models is essential to improve

the fit of the model. Covariates are essential because they can significantly alter the number of classes formed, the probability of an individual being included in a specific class, and the criteria used to create each class. Therefore, GGMM allows the testing of models that investigate more complex relationships among variables, thus providing a more appropriate statistical approach meeting the multifaceted demands of substance abuse research.

Applying Person-Centered Methods to Alcohol Abusers

Witkiewitz, in conjunction with other colleagues, conducted secondary data analyses on alcohol abusers undergoing outpatient treatment (Witkiewitz & Masyn, 2008; Witkiewitz et al., 2007). These three studies discovered three different post-treatment drinking trajectories: infrequent moderate, prolapsed, and frequent heavy drinkers. These series of studies demonstrated the possibility of finding distinct classes among alcohol treatment outcomes based on longitudinal data. Additionally, Witkiewitz's work on secondary data analyses has demonstrated the value of identifying classes and variables that predict treatment success among the classes (Witkiewitz & Masyn, 2008; Witkiewitz et al., 2007). Witkiewitz (2008) found that better coping over time was related to less frequent drinking. Also, individuals with higher severity scores were more likely to be classified as the heaviest, most frequent drinkers and had the worst outcome. With this type of statistical analysis, Witkiewitz et al. (2007, 2008) provided evidence and support for some of the original Project MATCH (matching alcoholism treatment to client heterogeneity) hypotheses (Project Match Research Group, 1998). Individuals with low self-efficacy who received cognitive-behavioral treatment performed better than individuals who also had low-efficacy and received motivational interviewing

(Witkiewitz et al., 2007). Also, clients with social networks supportive of drinking had better outcomes when they were assigned to the twelve step program (Wu & Witkiewitz, 2008).

Guided Self-Change Treatment Model: Individual and Group Settings

Guided Self Change (GSC) is a brief, outpatient treatment that uses both motivational interviewing and cognitive-behavioral techniques to facilitate change in individuals' addictive behaviors (Sobell & Sobell, 1993; Sobell & Sobell, 2005). The GSC model has been extensively evaluated and found to be an empirically supported, cost-effective treatment for problem drinkers. Guided Self Change uses Motivational Interviewing (MI) techniques to enhance internalized motivated change in individuals with an alcohol problem (Miller & Rollnick, 2002). The use of personalized feedback is an important component of MI, in which clients are presented with personalized information about their drinking levels, national norms, and health risks to increase motivation to change. Self-monitoring logs are used in GSC both for data collection, and to provide clients with feedback about their changes. Another feature of GSC is based on Bandura's cognitive social learning theory which suggests that people will be more committed to self-created rather than assigned goals (Bandura, 1986). Because research demonstrated that alcohol abusers will select their own treatment goal, regardless of therapist instruction (Sobell & Sobell, 1995), GSC allows clients to choose their treatment goal, be it abstinence or low-risk drinking. Clients are provided advice about risks and limits, and they are informed of any contraindications to drinking. Through homework, clients perform a functional analysis of their drinking by identifying high-risk situations and the consequences of drinking in those situations. Clients also develop their

own treatment plans by generating options and action plans for changing their drinking. Finally, GSC also involves a cognitive component of relapse prevention to offer clients a realistic perspective on change and tools for managing and conceptualizing possible setbacks in their recovery process.

Several studies have found that GSC delivered as an individual format is associated with outcomes comparable to other brief treatment interventions, yielding about a 50% reduction in alcohol consumption after 1 year of treatment (Sanchez-Craig, Neumann, Souzaformigoni, & Rieck, 1991; Sanchez-Craig, Spivak, & Davila, 1991; Sobell & Sobell, 1995). Only one study has examined the efficacy of the GSC model in a group format (Sobell et al., in press). The results of that study, which serves as the database for the secondary data analyses reported here, found no significant outcome differences between individual and group treatment; however, the group format resulted in a cost savings of 41% compared to individual treatment.

The few other studies that have compared individual and group formats using MI or CBT in alcohol abusers have similarly found that both delivery methods are effective in reducing alcohol use (Duckert, Amundsen, & Johnsen, 1992; Graham et al., 1996; Marques & Formigoni, 2001; Weiss et al., 2004). However, some differences in non-drinking outcome variables have been found. For example, Graham et al. (1996) found that compared to individual treatment, clients who were assigned to a relapse prevention group as an aftercare had better levels of psychosocial functioning.

In summary, the GSC dataset available for the present analyses provides a unique opportunity to investigate the nature of GSC treatment outcomes in problem drinkers, and to identify variables associated with different types of outcomes. The latter relationships

could suggest client-treatment matching hypotheses for future studies and could perhaps identify clients for whom GSC treatment is particularly well suitable.

Predictors of Treatment Outcomes

The identification of variables associated with good and with poor outcomes is important for suggesting client-treatment matching strategies. Although studies investigating the relationship of pretreatment and within-treatment factors to outcomes do not provide evidence of causality, they can provide a basis for predicting outcomes and also can stimulate thinking about mechanisms of change (i.e., what might explain the relationship of a particular factor to a good outcome?). The following various factors will be examined as predictors in the present study.

Drinking Patterns of Alcohol Use

Alcohol consumption is a primary domain of dependent variables in the assessment of alcohol treatment outcomes (Allen, Litten, & Anton, 1992). Several methods have been used to quantify drinking, including retrospective quantity-frequency questionnaires, self-monitoring, calendar-based timeline reconstruction, and retrospective grids representing a typical period (Miller & Del Boca, 1994). Most outcome studies have aggregated alcohol consumption variables into categories (e.g., drinks per day, number of days abstinent, number of drinking days per week) that exclude between- and within- individual variation. These variables usually summarize individuals' alcohol consumption over a specific time period. An instrument that allows the examination of patterns over time is the Timeline Followback (TLFB), a calendar-based retrospective method to assess daily alcohol consumption that yields a variety of outcome variables (e.g., daily drinking total, monthly drinking total, number of days on which drinking

occurred, number of drinks per drinking day, maximum number of drinks in 1-day, maximum number of continuous abstinent days; Sobell & Sobell, 1992). Although TLFB assessment data could be useful for identifying drinking patterns and change in patterns, most studies aggregate the longitudinal data and do not examine change over time. The TLFB's unique ability to generate information regarding the change process of alcohol abusers over time is important because alcohol abusers display a high level of drinking pattern fluctuation (Sobell & Sobell, 2002).

Drinking patterns have been classified using a host of different methodologies and operationalizations of categories. The inconsistencies across studies make it very difficult to compare investigations. In the literature, drinking patterns are often divided into categories such as "light," "heavy," and "excessive," with the operationalization of the definitions shifting across studies (Sobell & Sobell, 1982). For example, Cahalan (1987) confusingly classified "heavy" drinkers as those who drank two-three times a month with five or more drinks nearly every time or more than half the time or those who regularly drank three or more drinks a day. In contrast, other authors such as Fear and colleagues (2007) used psychometrically proven measures such as the Alcohol Use Disorder Identification Test (AUDIT) to classify individuals as heavy drinkers.

The terms binge, periodic, and bout drinking have also been used to classify drinking patterns, again with variations across populations and studies. In nonclinical samples, binge drinkers are considered to be those who drink at least five (for men) and four (for women) drinks in a day at least once in two weeks (Wechsler, Lee, Kuo, & Lee, 2000). However, this definition has little value in clinical populations since these individuals often consume five or more drinks in a day (Kahler, Epstein, & McCrady,

1995). Therefore, investigators, such as Connors, Tarbox, and McLaughlin (1986), classified bout drinkers as those who drank for several days, weeks, or months, separated by periods of abstinence. Still, others suggest that it is more effective to classify individuals as binge drinkers by estimating their blood alcohol concentration (BAC), since there are a number of personal aspects (e.g., gender, weight, & height) that determine the amount a person needs to drink to reach intoxication (Perkins, Linkenbach, & Dejong, 2001). Similarly, Schuckit (1998) has advocated using other variables, such as levels of intoxication, time intoxicated, and functional impairment to define binge drinkers.

Steady drinking is another term that has been used in the literature to classify alcohol abusers with fluctuations across authors and studies. Some researchers classify steady drinkers as those who drink approximately 5 times per week (Corrigan & Butler, 1991). In contrast, Marlatt and Miller (1984) defined steady drinking as drinking heavily at least once per week, focusing on the importance of drinking the same amount each occasion separated by periods of abstinence.

Historically, there has been huge variability in the way drinking patterns have been defined. Timeline Followback data have been used in two different studies to empirically identify four drinking categories in two different samples: binge, episodic, sporadic, and steady (Epstein, Kahler, McCrady, Lewis, et al., 1995; Epstein, Labouvie, McCrady, Swingle, & Wern, 2004). These categories were based on percentage of total drinking days and abstinent days, and specific clustering of light, moderate, and heavy drinking days using the TLFB. This type of classification involved a complex analysis that combined number of drinks per day with patterns of use over time. Although

including temporal variation, this method still provides a categorical rather than a continuous approach for the classification of alcohol abusers. Categorical approaches provide less information (i.e., everyone within categories is treated alike) than continuous approaches where individuals are considered by the extent to which they have same characteristics. An alternative approach providing reliable classes for post-treatment data involves a person-centered statistical approach for data analysis (Witkiewitz, 2008; Witkiewitz & Masyn, 2008; Witkiewitz et al., 2007). As mentioned earlier, in three studies using a person-centered approach, the same three drinking trajectories were obtained with post-treatment longitudinal data: infrequent moderate, prolapsed, and frequent heavy drinkers. Trajectory pattern findings for alcohol abusers based on pre-treatment TLFB data have not been conducted using a person-centered statistical approach.

Problem Severity Levels

Severity of AUD involves not only the amount of consumption, but also the impact the use has on the individual's life. Several studies have documented that problem severity is related to treatment outcomes (Akerlind et al., 1988; Hesselbrock et al., 1987; John et al., 2003; Shaw et al., 1990). The negative consequences of alcohol abuse can have a substantial impact on emotions, occupation, legal matters, financial situation, psychological wellbeing, and interpersonal relationships.

As is typical of most health problems, studies have found that heavier alcohol use and more psychological and social alcohol-related problems are associated with a lower likelihood of improvement after treatment (e.g., Armor & Meshkoff, 1983; Carroll et al., 1993; Hesselbrock et al., 1987; John et al., 2003; Moos & Moos, 2006; Moos et al., 2001;

Moos et al., 2002; Shaw et al., 1990). Some of the severity indicators that have been examined are length of the problem, frequency and quantity of alcohol use, history of alcohol treatment, and the abuse of other substances (Booth et al., 1991; Moos et al., 2001; Pettinati et al., 1999; Phibbs et al., 1997). Other studies have found that individuals with more alcohol dependence symptoms are more likely to show a rapid fluctuation in their drinking patterns (Babor et al., 1987; Witkiewitz, 2008). With regard to psychosocial functioning, lack of social support, legal history, aggressive behaviors, and emotional and interpersonal difficulties have all been related to relapse (Akerlind et al., 1988; Gordon & Zrull, 1991; John et al., 2003; Marlatt & Gordon, 1985; Moos et al., 2001).

Even though the research strongly suggests an inverse relationship between problem severity and outcomes, the majority of studies have been done using severely dependent alcohol populations. Only two studies have involved problem drinkers as part of their sample (Hesselbrock et al., 1987; Witkiewitz, 2008). Thus, the relationship of problem severity to outcomes with the restricted range of severity associated with problem drinkers is relatively unexplored.

Finally, no longitudinal studies were found examining the relationship of negative consequences to drinking pattern changes. It is not known whether specific alcohol-related consequences predispose individuals either to follow a stable pattern of change or to display major fluctuations in their drinking patterns.

Goal Choice

The primary goal for problem drinkers in alcohol abuse treatment is to achieve either abstinence or low-risk levels of alcohol consumption within recommended

guidelines. In some studies, the goal is set by the treatment program (e.g., Project MATCH 1993), but as already stated, the evidence demonstrated that, ultimately, the goal is chosen by the client (Sobell & Sobell, 1995). The National Epidemiologic Service on Alcohol and Related Conditions (Dawson, Grant, Stinson, Chou, Huang, & Ruan, 2005) found that over the long run low-risk drinking recoveries are about as common as abstinence recoveries even for individuals who previously met alcohol dependence criteria.

Only a few studies have investigated how individuals who choose low-risk drinking versus abstinence goals differ at baseline with pre-morbid levels of alcohol use and severity levels having received the most attention. Individuals who choose moderation as their drinking goal tend to have a primary diagnosis of mild to moderate alcohol dependence, whereas individuals who tend to choose abstinence are more likely to have a more severe alcohol dependence diagnosis (Adamson & Sellman, 2001; Sobell & Sobell, 1995). Those with a goal of moderation also tend to have had a drinking problem for a shorter period of time than those who opt for abstinence (Pachman, Foy, & Van Erd, 1978).

Psychological and social stability have also been found to be associated with the choice of abstinence or a low-risk drinking goal. Individuals with employment and occupational stability tend to choose a low-risk drinking goal (Heather & Robertson, 1981; Rosenberg, 1993). Similarly, Nordstrom and Berglund (1987) discovered in an inpatient Swedish sample that greater baseline social stability was more frequent among those who chose moderation versus abstinence. Regarding psychological functioning, a

study found that low-risk drinkers have a greater sense of well-being than abstainers (Adamson & Sellman, 2001; Heather & Robertson, 1981).

Demographic variables such as gender, age, and education have also been found to be related to goal choice. Adamson and Sellman (2001) found that more educated individuals were more likely to choose a moderation goal. Individuals who choose moderation also tend to be younger than those who choose abstinence (Booth et al., 1984; Heather & Robertson, 1981; Polich et al., 1981). Considering gender, several studies have found that a greater proportion of women than men select a moderation goal (Edwards et al., 1988; Foy, Nunn, & Rychtarik, 1984).

Concerning outcomes associated with goal choice, most studies have found no differences in outcomes between individuals who choose abstinence versus moderation (Booth et al., 1984; Booth et al., 1992; Ojehagen & Berglund, 1989; Orford, Oppenheimer, & Edwards, 1976; Sanchez-Craig et al., 1984). Only one study found selecting a moderation goal to be associated with better outcomes after treatment (Pachman et al., 1978). Not surprisingly, in two studies, individuals who chose abstinence goals had a higher rate of abstinent days at outcome than those who chose a low-risk drinking goal (Foy et al., 1984; Hodgins, Leigh, Milne, & Gerrish, 1997). In both cases, the participants had high severity pre-morbid levels of alcohol problems.

CHAPTER III:

Method

Participants

Participants were part of a randomized controlled trial that involved individuals with either a primary alcohol problem ($n = 231$) or a primary drug problem ($n = 56$; Sobell et al., in press). They had voluntarily entered outpatient treatment at the GSC Unit of the Addiction Research Foundation (ARF) in Toronto, Canada. Treatment was provided at no cost. Only participants with a primary alcohol problem were included in the present secondary analysis ($n = 231$). The present secondary data analysis was approved by the Nova Southeastern University Institutional Review Board (IRB), and the clinical study was approved by the University of Toronto/Addiction Research Foundation IRB.

Eligibility criteria for the study included the following (Sobell et al., in press): (a) volunteered (via a signed informed consent form) to participate in a brief treatment intervention; (b) were 18 years of age or older; (c) had not been mandated to treatment (e.g., employer, courts); (d) had no evidence of organic brain damage as determined by age-adjusted scores on the Trail Making Test and Digit Symbol subscale of the WAIS (Wilkinson & Carlen, 1980); (e) had adequate reading abilities as indicated by the Wide Range Achievement Test (Jastak & Jastak, 1965); (f) were not currently in psychiatric or psychological treatment; (g) were living in stable housing; and (h) agreed to be available for a 12-month post-treatment follow up.

Since the GSC treatment was designed for individuals with a mild to moderate severity level of substance use disorders, criteria were also used to exclude individuals

with a history of severe dependence (Sobell et al., in press): (a) history of major alcohol withdrawal symptoms (e.g., hallucinations, seizures, delirium tremens) by self-report or medical history; (b) a score of ≤ 25 on the Alcohol Dependence Scale (Skinner & Allen, 1982); (c) on average, drank ≥ 12 standard drinks (1 standard drink = 13.6 g absolute ethanol) on ≥ 5 days per week during the year prior to treatment (M. B. Sobell, Sobell, & Leo, 2000); (d) a score of >15 on the Drug Abuse Screening Test-20 (Skinner, 1982); (e) intravenous (IV) drug use because IV drug abusers typically have more serious drug problems (Gavin, Ross, & Skinner, 1989; Skinner, 1982); or (f) primary drug problem was heroin.

Because GMM does not allow for missing data, only data from the 200 participants who completed the first 6-month TLFB follow-up were included in the analysis. Since there were data collected for 231 total participants with a primary alcohol problem, statistical comparisons were performed comparing those with full 6-month TLFB data to those without TLFB data. A Bonferroni adjustment was used to maintain the family wise error rate at a .05 level. Independent *t*-tests were conducted for continuous variables and *z*-score tests for the dichotomous variables. This allows for evaluation of demographics and alcohol history differences for participants who completed and for those who did not complete the first 6-month TLFB follow-up (see Table 3.1). The Levene's test for equality of variance was shown to be significant for one variable, years of education; therefore, adjustment on the *t*-statistic was performed for this variable. No significant differences were found for any of the variables tested.

Table 3.1

Pretreatment Characteristics

Variable	Participants who completed 6-month TLFB follow-up (<i>n</i> = 200)	Participants who did not complete 6-month TLFB follow-up (<i>n</i> = 31)	T ^a or Z ^b
Mean (<i>SD</i>) age (yrs)	43.16 (11.16)	39.90 (11.29)	1.51 ^a
Mean (<i>SD</i>) education (yrs)	14.52 (2.56)	13.94 (2.74)	1.11 ^a
Full-time or self-employed (%)	73.5%	54.8%	1.92 ^b
Male (%)	67.5%	64.5%	0.12 ^b
Married (or common-law) (%)	57.0%	48.4%	0.70 ^b
Mean of (<i>SD</i>) % of days use any alcohol	70.18 (27.67)	64.52 (29.50)	1.05 ^a
Mean (<i>SD</i>) of standard drinks per day	6.65 (3.44)	7.45 (4.01)	-1.22 ^a
Mean (<i>SD</i>) alcohol arrests	0.56 (1.18)	0.45 (0.77)	0.47 ^a
Mean (<i>SD</i>) alcohol hospitalizations	0.16 (0.76)	0.10 (0.30)	0.46 ^a
Goal choice – low-risk drinking (%)	73.50%	91.7% ^c	1.89 ^b
Individual Treatment (%)	50.0%	61.3%	0.98 ^b

Note. There were no statistically significant differences between participants who completed and who did not complete the first 6-month TLFB follow-up.

^aT = two-tailed independent sample *t*-tests. ^bZ = two-tailed independent sample *z*-scores.

^c*n* = 12.

**p* < .001, alpha level adjusted for multiple tests.

Procedure

As described in Sobell et al. (in press), following the screening and initial assessment participants were randomly assigned to one of the two treatment modalities (individual or group). During the first contact, clients completed a battery of forms and questionnaires related to demographics and alcohol-related history variables. Alcohol clients, for whom there were no medical contraindications, were also asked to complete a goal statement form (i.e., abstinence or low-risk drinking).

Participants that were randomized to the individual format received treatment from a single therapist, while every group had two therapists (Sobell et al., in press). Both conditions consisted of an assessment and four sessions. Individual treatment sessions were 60 minutes, while group sessions were 90 to 120 minutes. Group size ranged from 4 to 8 clients (no new members were allowed after Session 1).

After the fourth GSC session, follow-up interviews were scheduled at 6 and 12 months post treatment (Sobell et al., in press). Research assistants, who were blind to participants' treatment conditions, conducted the follow-up interviews. Participants interviewed at the ARF were paid \$25.00 for their follow-up participation. With the clients' permission, collaterals (e.g., relatives, friends) were interviewed by phone at 6- and 12-months post-treatment to corroborate clients' self-reports of substance use and consequences. Collaterals also provided reports about negative consequences related to clients' substance use.

Baseline and Outcome Measures

Assessment Questionnaire

A semi-structured clinical interview was used to collect demographic information (e.g., education, gender, age), substance abuse history (e.g., years of problem, hospitalizations, number of arrests), as well as alcohol-related consequences. Individuals indicated if they had experienced negative consequences as a result of drinking in the year prior to treatment in the following areas: health, cognitive impairment, affective impairment, interpersonal, vocational, legal, financial problems, and aggression.

Timeline Followback (TLFB)

The TLFB employs a retrospective, self-report calendar format and memory prompts to aid in a subject's day-to-day recall of a targeted behavior over a specified time window (i.e., weeks, months; Agrawal, Sobell, & Sobell, 2007; Sobell & Sobell, 1992). The TLFB is one of the most psychometrically sound instruments currently available for retrospectively assessing daily drinking (Agrawal et al., 2007). In this study, the TLFB was used to collect drinking data for 12-month pretreatment and the 6- and 12-month follow-ups (Sobell et al., in press). Little was known about the representativeness (i.e., stability) of different TLFB time windows until a recent study using assessment data from 825 problem drinkers found that a 3-month interval (i.e., the 3 months prior to treatment entry) provided a satisfactory representation of pretreatment annual drinking for a sample of problem drinkers (Vakili, Sobell, Sobell, Simco, & Agrawal, 2008). The pretreatment data for the three months prior to entering treatment were used in the present analyses. However, research on the adequacy of time windows using the TLFB for follow-up has not been reported. For the analyses constituting the present study, TLFB

data for the first three months of follow-up were used in order to achieve a manageable size data set. It should be cautioned that early follow-up data, such as used here, may have less stability than longer term follow-up. Given the current state of research, it would be inappropriate to interpret the present findings as representing long-term outcomes.

Goal Statement

The Goal Statement form prompted participants to specify their drinking goal for the next 6 months (Sobell et al., in press). In particular, the first question asked whether the individual intended to abstain or engage in low-risk drinking (Sobell & Sobell, 1993). Those who chose the latter, then, answered several questions concerning the specific drinking limits in terms of average number of drinks per drinking day, maximum number of drinks per occasion, maximum number of days per month of drinking at the upper limit, the maximum number of drinking days per week, and the conditions under which drinking would (low-risk) and would not (high-risk) occur. All subjects who chose a low-risk goal were informed about low-risk drinking guidelines and those with medical contraindications to drinking were strongly advised to choose an abstinence goal.

Guided Self Change Treatment Components

The major treatment components involved the following: (a) the use of a MI style throughout treatment to increase and maintain clients' commitment to change; (b) personalized feedback to clients regarding their assessment results (e.g., extent of use, health risks); (c) decisional balancing to evaluate and consolidate motivation to change; (d) treatment goal choice by clients with advice about contraindications and low-risk drinking guidelines; (e) the use of self-monitoring logs within-treatment; (f) homework

assignments to help clients identify high-risk situations and then, develop options and action plans for those situations; and (g) cognitive relapse prevention techniques (Sobell et al., in press).

Group Treatment Procedure

Regardless of their treatment condition, all clients were treated using the same GSC procedure and assignments (Sobell et al., in press). The content of groups differed from individual in that the format of the interaction between group members occurred in a round robin discussion manner. Feedback and advice came mainly from the group members rather than the therapist, consistent with group processes (Dies, 1994; Yalom & Leszcz, 2005). Another difference between the individual and group treatment format was that group members did not receive as much time to discuss their homework and concerns as those assigned to the individual treatment. If a client missed a group meeting, he or she met with one of the therapists individually to review the components of that session.

Statistical Analysis

The Mplus v5.0 software program (Muthén & Muthén, 1998-2007) was used to estimate the GMM with and without covariates and the sequential GMM. This statistical package uses a maximum likelihood estimation with robust standard errors (called the MLR estimator in Mplus) to add robustness to non-normal data. This allows the error variance to differ over time, but keeps it constant for all individuals in the same category for each time period (Bollen, 2006). The first step in the analysis was to model the individuals' trajectories of post-treatment drinking frequencies and the average percentage of functional days per week. Functional days were defined as days when

individuals were abstinent or did not consume more than three drinks. This descriptive analysis then allowed each case to have a distinct intercept and slope to describe linear and non-linear trajectories of percentage of functional days within the 3 months after treatment (Bollen, 2006). The objective was to examine the various onsets and rates of change in order to allow GGM to fit linear and/or nonlinear latent curves.

Even though the TLFB was used to record the participant's level of daily drinking for a 12-month pre-treatment and follow-up period (Sobell et al., in press), as previously mentioned for data analysis purposes only the 3-month before treatment and after treatment data sets were used in the present study. In addition to evidence previously described showing that a 3-month pretreatment interval was sufficient for studies involving problem drinkers (Vakili et al., 2008), the main reason for using 3-month data was because a weekly aggregation of time-point data was used in the analyses, and time points have to be limited to decrease the complexity of the model as a result of the sample size.

The latent curves of GMM were set according to the most feasible number of trajectories observed in the data. Therefore, the models were fixed to a linear function and a quadratic model according to the individual trajectories (Bollen, 2006). After setting the different latent trajectories of change, the following four covariates were investigated to explore their effects on the growth factors and class membership: (a) pre-morbid level of alcohol use, (b) number of alcohol-related consequences, (c) goal choice, and (d) treatment modality. These models expressed the probability that an individual i was a member of class k as a function of the covariate x . Assigning one class as a reference allowed for the log odds estimation of class membership for each covariate.

These models also included regression of the growth parameters on the covariates, with the regression coefficient to vary across classes. Ultimately, the objective was to evaluate the covariates' effects on the growth factors within each category.

Since the GMM includes a number of model variations, it is essential to find the best fitting and the most parsimonious model that fits the data (Muthén, 2001b). The adjusted Bayesian Information Criterion (aBIC), the adjusted likelihood ratio test (LRT), and the bootstrapped likelihood ratio test (BLRT) were employed to accomplish this objective. The aBIC balances two components, maximum likelihood and model parsimony. According to the aBIC, a good model has a high likelihood value and uses the least number of parameters, with a low aBIC value indicating a better fitting model. The aBIC also considers the number of parameters and sample size in order to account for the complexity of the model. This method was recently found to be the best likelihood-based indicator of model fit for latent variable mixture models (Henson, Reise, & Kim, 2007). The LRT and BLRT models were 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 at least k classes (McLachlan & Peel, 2000; Nylund, Muthén, & Asparouhov, in press).

The second indicator, which examines the quality of group data classification, is the posterior probabilities. This is determined by locating the highest average posterior probability for individuals, which is found in the diagonal elements. Within each class, posterior probabilities are related to the likelihood that an individual endorses an indicator (Bucholz et al., 1996). These probabilities provide information on class membership assignment according to the indicators. The posterior probabilities are

summarized by the entropy measure (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993), with numbers closer to 1 indicating more precise classification. Finally, in order to choose the best model, the utility, distinctiveness, and interpretability of the classes yielded by each model were considered (Witkiewitz & Masyn, 2008).

Once the best model fit was selected, the second stage tested specific hypotheses regarding the relationship between the previously mentioned covariates (treatment modality, goal choice, number of negative alcohol-related consequences, and pre-treatment levels of alcohol consumption) in the prediction of drinking trajectories and trajectory class membership. The goals of the covariate analyses were twofold: (a) to assess the degree to which these covariates predict class membership, and (b) to evaluate the within-class effects of these covariates on the intercept and slope of each class. When covariates were added to the GMM models that had the same number of classes, the likelihood-ratio chi-square difference test was used. If the model with the covariate was found to be significantly smaller than the GMM without the covariate, the former model was concluded to show a better fit and was, therefore, preferable. A multinomial logistic regression was used to evaluate the association between the covariates and the latent class membership. Here, each covariate association was characterized by $k-1$ regression coefficients where k was the number of latent classes. Each coefficient represents the change in the log odds of being in a given class, relative to the reference class for a 1-unit change in the covariate. The significance of the coefficient as well as the corresponding odds ratios was calculated for each covariate. In addition, covariates were incorporated as predictors of within-class variation in growth trajectories using standard linear regression.

As an alternative analysis to aid in understanding the relationship between drinking severity levels at pre-treatment and follow-up, a sequential process GMM and a cross-tabulation chi-square analysis was conducted with SPSS v14.0. The two analyzed indicators of drinking severity level from the assessment data were the number of functional days for the 3-month pre-treatment TLFB and alcohol-related consequences. For the TLFB data, individuals' trajectories for the 3-month pre-treatment drinking data were modeled in order to understand the growth parameters of the GMM. To choose the best GMM, the same procedure was followed for the follow-up data. In the case of the alcohol-related consequences data, a LCA was conducted to yield the latent classes. For the Latent Class Analysis (LCA) models, both the Bayesian Information Criterion (BIC) and the BLRT have been shown to be the best indicators of the number of classes (Nylund et al., in press). The BIC balances two components, maximum likelihood and model parsimony (Schwartz, 1978). According to the BIC, a good model has a high likelihood value using the least number of parameters, thus resulting in a low BIC value and indicating a well-fitting model (BIC). The estimated item probabilities were used to attach substantive meaning to the latent classes by presenting the mean probability for each client endorsing an alcohol-related consequence in a given class. Both the LCA and the GMM determined different drinking-related classes prior to treatment to generate the class information necessary for understanding the relationship between pre-treatment alcohol severity levels and treatment outcome within a latent class framework.

A sequential process GMM with pre-treatment and follow-up TLFB drinking data was examined to evaluate individuals' class transitions. For each GMM, process growth factors were estimated according to the observed individual trajectories before

determining the latent growth factors of the model. Each of the growth factors was influenced by a latent class variable specific to the process, causing the means of the growth factors to change across classes. Posterior probabilities and transition probabilities were used to determine meaningful relationships between classes. Probabilities closer to one indicated a higher relationship among the classes, meaning that an individual had a higher chance to transition from a specific pre-treatment latent class to a post-treatment one. Regarding alcohol-related consequences, the classes obtained by the LCA were related to the latent classes obtained by the GMM model for the TLFB follow-up data by conducting a cross-tabulation analysis in SPSS v14. In addition, posteriori class probabilities for the two models were associated to account for some of the error variance in class membership assignments. The relationship between the two latent classes was determined by the statistical significance of chi-square at an alpha level of .05.

CHAPTER IV:

Results

Growth Mixture Models for TLFB Follow-up Data

After examining the individual trajectories of follow-up drinking data, three growth factors were used in the GMM (Figure 4.1) corresponding to the intercept (β_0), linear slope (β_1), and nonlinear quadratic slope (β_2). The fit indicators for the 1- to 6-class trajectories models are shown in Table 4.1, with specific class trajectories shown in Figure 4.2. The aBIC rate of decrease is highest when comparing differences from a 1- to a 2-class model (8BIC = 94.22); then decreases 46.78 points from a 2- to a 3-class model.

From a 3- to a 4-class model this difference increases once again (8BIC = 74.90). The difference between a 4- and a 5-class model decreases and then, increases again between a 5- and a 6-class model (8BIC = 39.99 and 77.62, respectively). Since the largest difference occurred between the 1- and 2-class models, a 2-class model, therefore, demonstrates the most parsimonious, best fitting model. Although, in general, all the models showed high entropies, the 4-, 5-, and 6-class models showed the highest entropy (0.98). The BLRT indicates that all the class models fit significantly well; however, based on the LRT indicator a 2-class model is the only one that shows a good fit. As seen in Table 4.1, the 2-class model appears to strike the best balance between parsimony and fit, providing a significantly better overall fit than the 1-class model according to the LRT/BLRT outcomes. The 4-class model also appears to be a good option according to all indicators except the LRT method. For both, a 2-class model and a 4-class model, a theoretical explanation fits well.

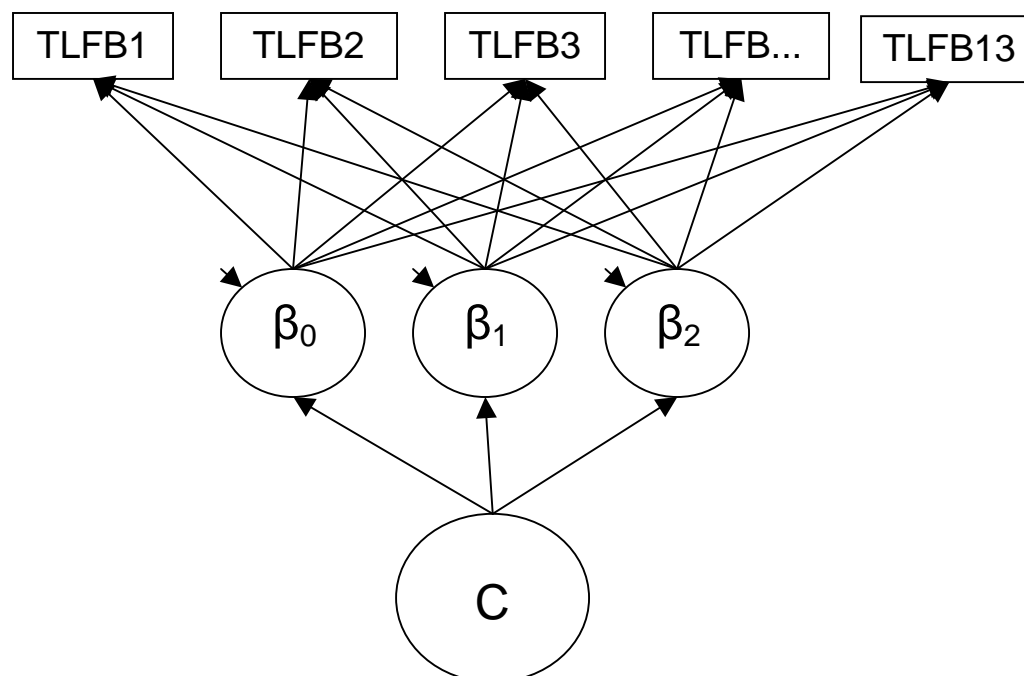


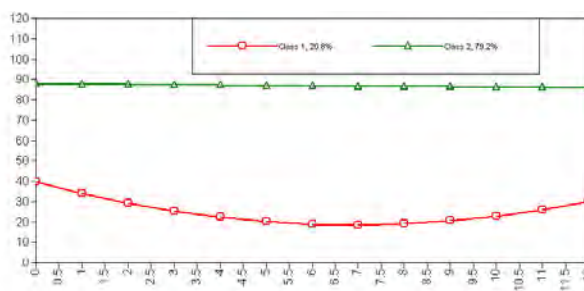
Figure 4.1. Growth Mixture Model for Pre-Treatment and Post-Treatment TLFB Data.

Table 4.1

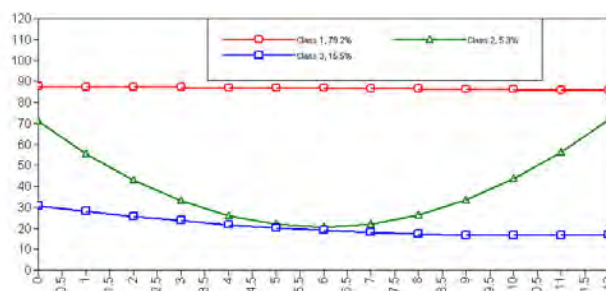
Model Fit for Growth Mixture Models

Outcome	Log-likelihood	Entropy	aBIC	LRT	BLRT p -value
k-class	(# free				
model	parameters)				
1-class	1882.38 (22)	--	22009.72	--	--
2-class	-10801.24 (14)	0.93	21632.31	89.48, $p = .002$	93.71, $p < .0001$
3-class	-10902.19 (30)	0.95	21868.72	52.88, $p = .28$	55.36, $p < .0005$
4-class	-10860.45 (34)	0.98	21793.82	97.63, $p = .16$	102.22, $p < .0005$
5-class	-10835.66 (38)	0.98	21753.83	63.98, $p = .28$	66.99, $p < .0005$
6-class	-10793.06 (42)	0.98	21676.21	46.521, $p = .09$	48.71, $p < .0005$

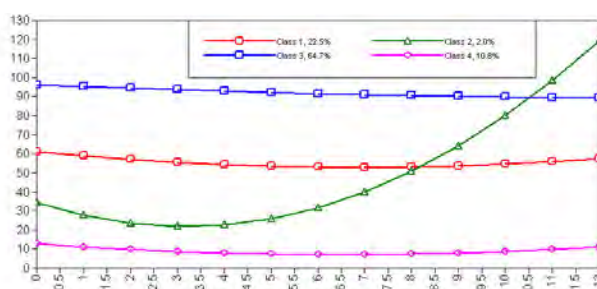
(a) 2- Class Model



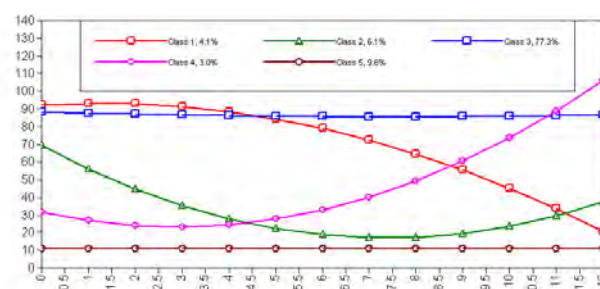
(b) 3- Class Model



(c) 4- Class Model



(d) 5- Class Model



(e) 6- Class Model

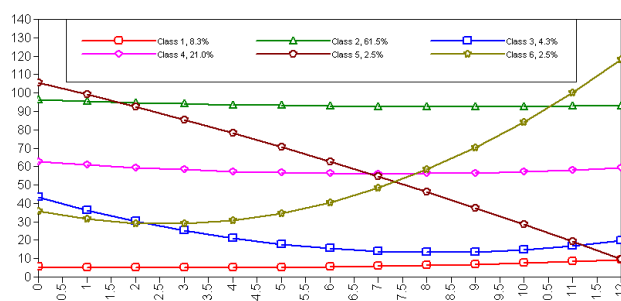


Figure 4.2. Change Trajectories for the 2-Class to the 6-Class Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Two-Class Model for TLFB Follow-up Data

Figure 4.3 shows the trajectories for the estimated means of the 2-class model. This model represents two distinct groups of participants based on their number of functional days after treatment. The two classes can be divided into high functioning clients (HFC; $n = 161$, 80.5% of the total sample) and low functioning clients (LFC; $n = 39$, 19.5% of the total sample). Figures 4.4a and b show the estimated means of the individuals' observed values for HFC and LFC, respectively. The HFC group is characterized by individuals who, as a group, have relatively high stable rates of functioning throughout the 3-month follow-up (estimated means of percentage of functional days ranged from 85.40 to 89.31), while the LFC group represents those who had relatively poor functioning after treatment (estimated means of percentage of functional days ranged from 15.13 to 38.62). Table 4.3 represents the parameters of the growth mixture modeling for each of the two classes. Within the high functioning group, neither the linear nor quadratic slopes were significant ($\beta_1 = -0.19$, $p = .56$; $\beta_2 = 0.00$, $p = .93$), indicating that individuals generally had a similar number of average functioning days across the 3-month follow-up. This suggests that participants in this class had a high level of stability in their alcohol use after treatment. In contrast, both the linear and quadratic slopes for the low functioning group were statistically significant ($\beta_1 = -6.09$, $p < .001$; $\beta_2 = 0.44$, $p < .001$), thus indicating fluctuating of drinking patterns during the first three months of follow-up.

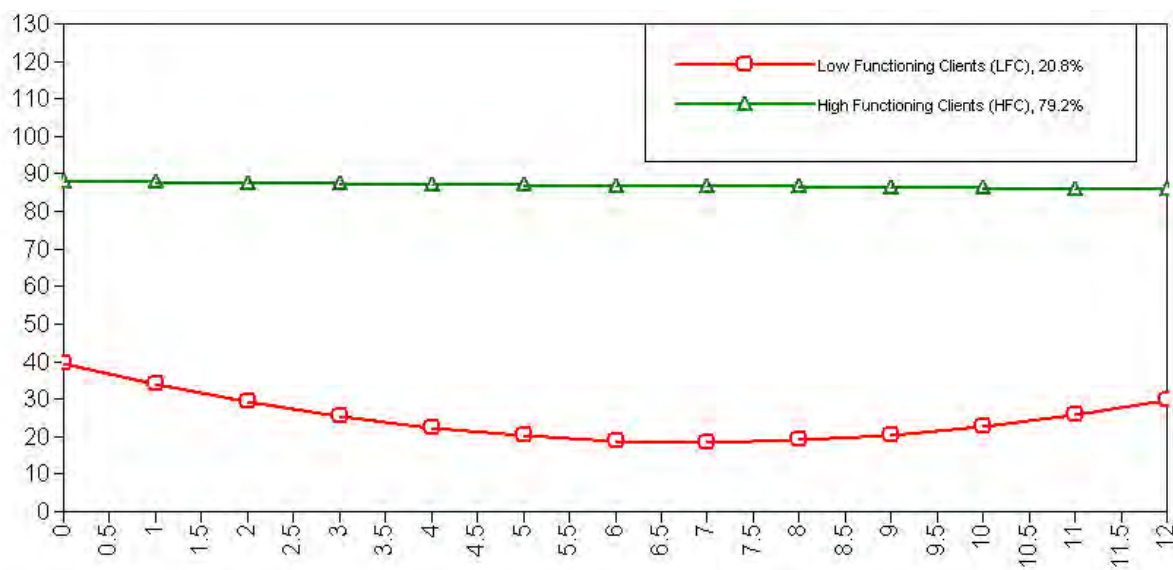
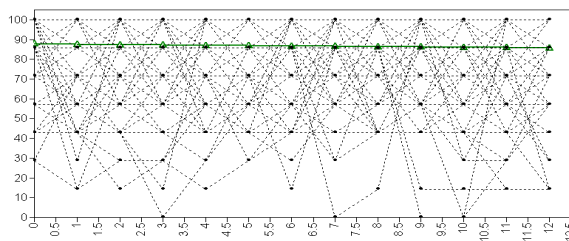


Figure 4.3. Estimated Means for Change Trajectories for the 2-Class Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

(a) High Functioning Clients (HFC)



(b) Low Functioning Clients (LFC)

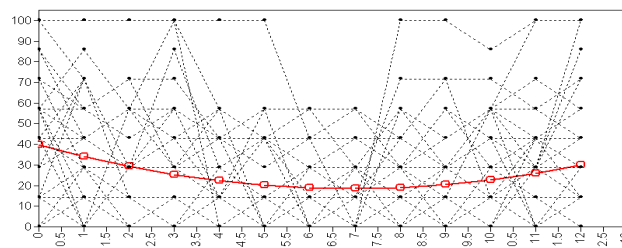


Figure 4.4. Estimated Means and Observed Individual Values for HFC and LFC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Table 4.2

Growth Factor Means for Each Drinking Class

Drinking Classes	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
High Functioning Clients (HFC)	87.85*	-0.19	0.00
Low Functioning Clients (LFC)	39.58*	-6.09*	0.44*

* $p < .001$ *Four-Class Model for TLFB Follow-up Data*

Figure 4.5 illustrates the trajectories for the estimated means of the 4-class model. The four classes can be described as high functioning clients (HFC; $n = 131$, 64.7%), low functioning clients (LFC; $n = 19$, 10.8% of the total sample), fluctuating clients (FC; $n = 46$, 22.5% of the total sample), and delayed-changers (DDC; $n = 4$, 2.0% of the total sample). As with the 2-class model, the HFC group is characterized by individuals who did well during follow-up (estimated means range from 89.29 to 91.84; see Figure 4.6a), and the LFC represent the people who did not improve at follow-up (estimated means range from 5.06 to 14.99; see Figure 4.6b). The DDC group consisted of individuals who, immediately after treatment, had low functioning days (estimated mean = 39.24), but, then, increased their number of functional days as the follow-up period progressed

(estimated mean = 99.99; Figure 4.6c) The participants in the FC group represent individuals who generally had a middle range of functional days across the 3-month follow-up (estimated means range from 52.29 to 63.42). However, it should be kept in mind that this pattern fit only a very small number of participants. As shown in Figure 4.6c, this group fluctuated between weeks of high and low functioning throughout the follow-up. Table 4.3 represents the parameters of the GMM for each of the four classes. Unlike the HFC group's outcome for the 2-class model, the linear slope is negative and significant ($\beta_1 = -0.99, p = .007$) indicating that individuals in this category slowly decreased their functional days as the weeks progressed. Regarding the LFC group, neither the linear nor the quadratic slopes were significant indicating that members had a constant level of low-functioning days across the 3-month follow-up ($\beta_1 = -1.73, p = .10; \beta_2 = 0.13, p = .007$). Within the FC category results showed that individuals typically had a stable number of days within the middle range of functioning days percentages with a significant and slow improvement according to the linear slope ($\beta_1 = -2.39, p = .04$). However, when examining the observed values for the FC group (see Figure 4.6c), it should be noted that these trajectories represent individuals whose functional days across the weeks vary with no identifiable pattern. According to both the linear and quadratic slopes, the clients in the DDC group generally appear to have low functional days immediately after treatment, but improve as follow-up progresses ($\beta_1 = -8.02, p = .09; \beta_2 = 1.26, p = .001$). The quadratic slope also reveals that before these individuals improve, they have less functional days than when they completed treatment.

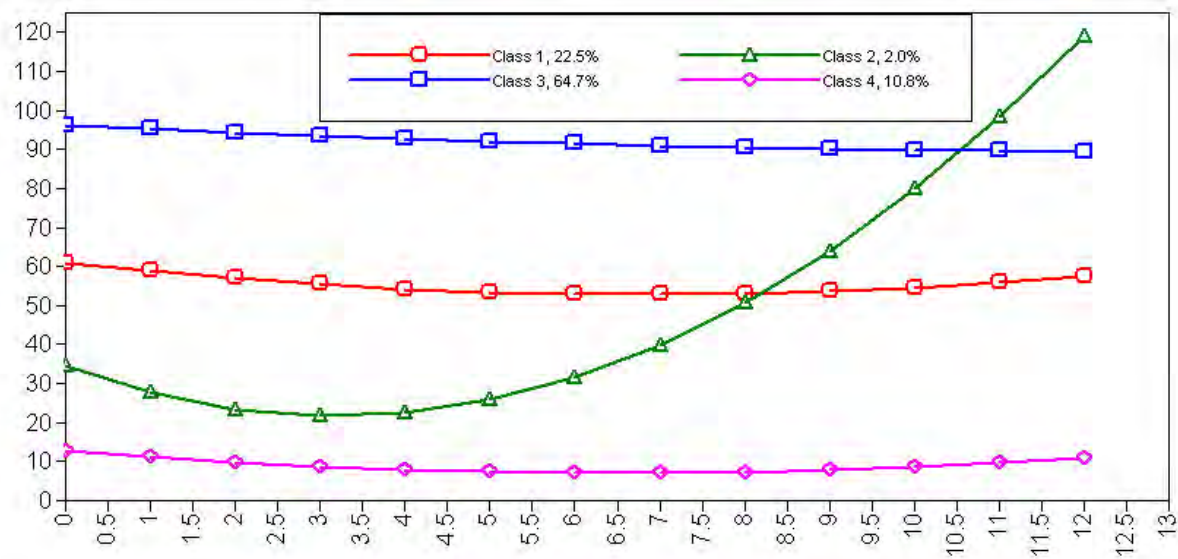
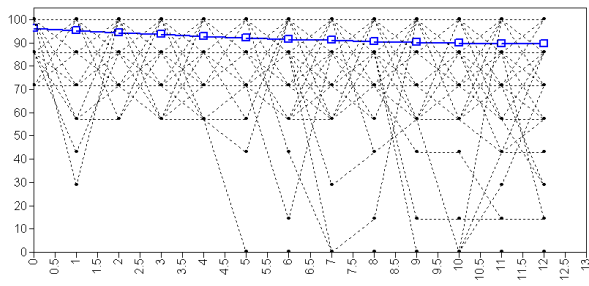


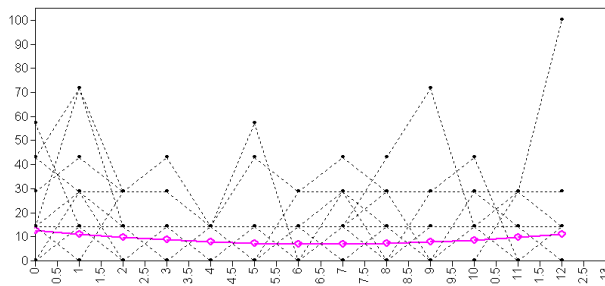
Figure 4.5. Estimated Means for the Trajectories of Change of a 4-Class Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data. Class 1 = LFC, Class 2 = FC, Class 3 = HFC, Class 4 =DDC.

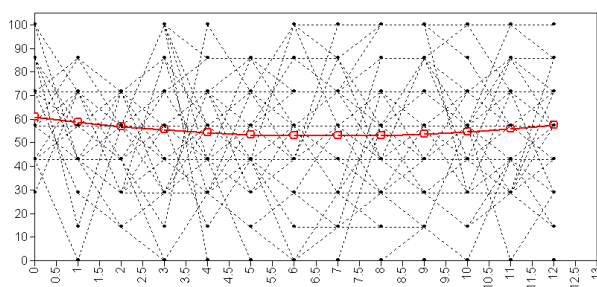
(a) High Functioning Clients (HFC)



(b) Low Functioning Clients (LFC)



(c) Fluctuating Clients (FC)



(d) Delayed-Changers (DDC)

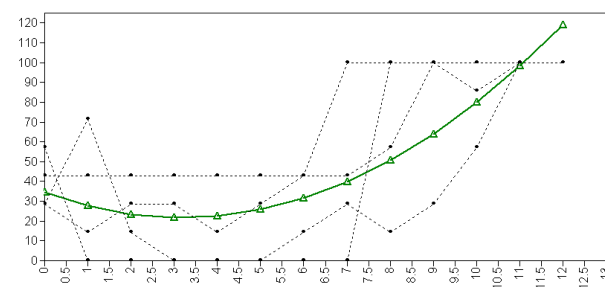


Figure 4.6. Estimated Means and Observed Individual Values for HFC, LFC, R, and SC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Table 4.3

Growth Factor Means for Each Drinking Class

Drinking Classes	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
High Functioning Clients (HFC)	96.18***	-0.99**	0.036
Low Functioning Clients (LFC)	12.71***	-1.73	0.13*
Fluctuating Clients (FC)	61.00***	-2.39**	0.18*
Delayed-Changers (DDC)	34.49***	-8.02*	1.26**

*** $p < .001$; ** $p < .05$; * $p < .1$

Growth Mixture Models with Covariates for TLFB Follow-up Data

Two-Class Model with Covariates

As indicated by Tables 4.4 and 4.5, for the GMM with covariates, the results show several significant relationships between the covariates and the within-class growth factors for the two-class model. Within the high functioning group ($n = 175$, 87.84%), individuals who chose an abstinence goal at intake finished treatment with a significant higher percentage of functional days than those who chose a moderation goal ($\beta_0 = -14.47$, $p < .001$). The estimated mean of percentage of functional days at post-treatment

for HFC who chose abstinence was 94.64%, whereas for individuals who chose moderation, it was 86.14%. This relationship remained stable across time since neither the linear nor the quadratic slopes were significant ($\beta_1 = -0.62, p = .35; \beta_2 = 0.07, p = .21$). Forty-two individuals with an abstinence goal versus 133 with a moderation goal were classified as HFC. Regarding pre-treatment data, HFC who finished treatment with lower functional days had a significantly higher number of alcohol-related consequences and drank 5 or more drinks per occasion on more days at intake than those who had a higher percentage of functional days after treatment ($\beta_0 = -2.76, p = .007$, and $\beta_0 = -0.25, p = .002$ respectively). Estimated means of follow-up functional days for individuals who endorsed a higher number of consequences at intake was 82.86% versus 91.43% for individuals who endorsed a lower number of consequences. In the same direction, estimated means of functional days for individuals who, at pretreatment, had a higher number of days when they consumed 5 or more drinks was 67.14% versus 94.29% for individuals with a lower number of days consuming 5 or more drinks. As with goal choice, this relationship was stable across time for the number of alcohol-related consequences ($\beta_1 = 0.06, p = .78; \beta_2 = 0.01, p = .59$). However, the linear and quadratic slope for the number of days where 5 or more drinks were consumed was significant ($\beta_1 = -0.02, p < .05; \beta_2 = 0.002, p < .05$), indicating that individuals who had a higher number of days drinking 5 or more drinks in one occasion prior to entering treatment, tended to show more variability of percentage of functional days across the follow-up period (see Figure 4.7).

Regarding LFC ($n = 25, 12.06\%$), there was only a significant relationship between alcohol related consequences and the intercept ($\beta_0 = 18.26, p < .001$, see Table

4.5). In contrast to the HFC, LFC who had a higher number of alcohol-related consequences showed better outcome after treatment (estimated mean = 97.62%) than individuals with lower number of alcohol-related consequences (estimated mean = 42.86%). This relationship was sustained over time ($\beta_1 = -0.29, p = .82; \beta_2 = -0.12, p = 0.28$). Cautious interpretation should be made for this last finding as the sample size for this group was small. In addition, based on covariates significant results were obtained from the multinomial logistic regression of class membership. Table 4.6 shows the odds ratio for the covariates' effects on class membership. Here, individuals who consumed less than 5 or more drinks at intake were more likely classified as HFC.

Table 4.4

Parameter Estimates for Growth Factors Regressed on Covariates for High Functioning Clients (HFC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	0.72	-0.88	0.03
Goal Choice	-14.47**	-0.62	0.07
Number of Consequences	-2.76*	0.06	0.01
Number of days consumed 5 or more drinks per day	-0.25*	-0.02*	0.002*

** $p < .001$; * $p < .05$

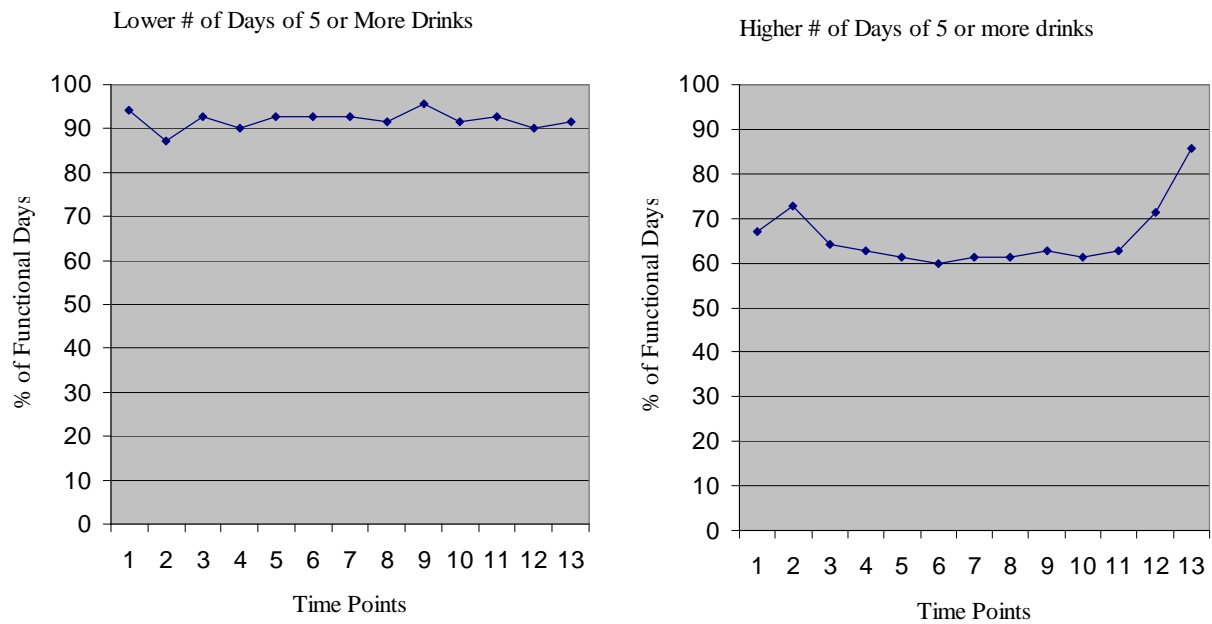


Figure 4.7. Estimated Means Comparison for Individuals in the HFG with High and Low Number of Days Consumed 5 or More Drinks.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Table 4.5

Parameters Estimates for Growth Factors Regressed on Covariates for the Low Functioning Clients (LFC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	-17.03	0.58	0.36
Goal Choice	0.09	3.20	-0.40
Number of Consequences	18.26**	-0.29	-0.12
Number of days consumed 5 or more drinks per day	-0.05	-0.06	0.01

** $p < .001$

Table 4.6

Odds Ratios (95% Confident Intervals) for the Covariates in the 2-Class Model

Covariates	OR ^a
Modality	1.27 (0.38 – 3.39)
Goal Choice	0.60 (0.19 – 1.89)
Number of Consequences	1.00 (0.76 – 1.30)
Number of days consumed 5 or more drinks	1.03 (1.01 – 1.05)*

* $p < .05$

^aHFC was the reference class

Four-Class Model with Covariates

In contrast to the two-class models, the classes in the four-class model changed as a result of the inclusion of the covariates. As seen in Figure 4.8, the four classes created were the high functioning clients (HFC; $n = 143$, 71.02% of the total sample), low functioning clients (LFC; $n = 34$, 17.75% of the total sample), fluctuating clients (FC; $n = 9$, 4.57% of the total sample), and deteriorating clients (DC; $n = 14$, 6.67% of the total sample). Similar to the 4-class model without covariates, this model has a high functioning, a low functioning, and a fluctuating class. However, this model does not include a delayed-change class, but rather a new class is created (DC; see Figure 4.9).

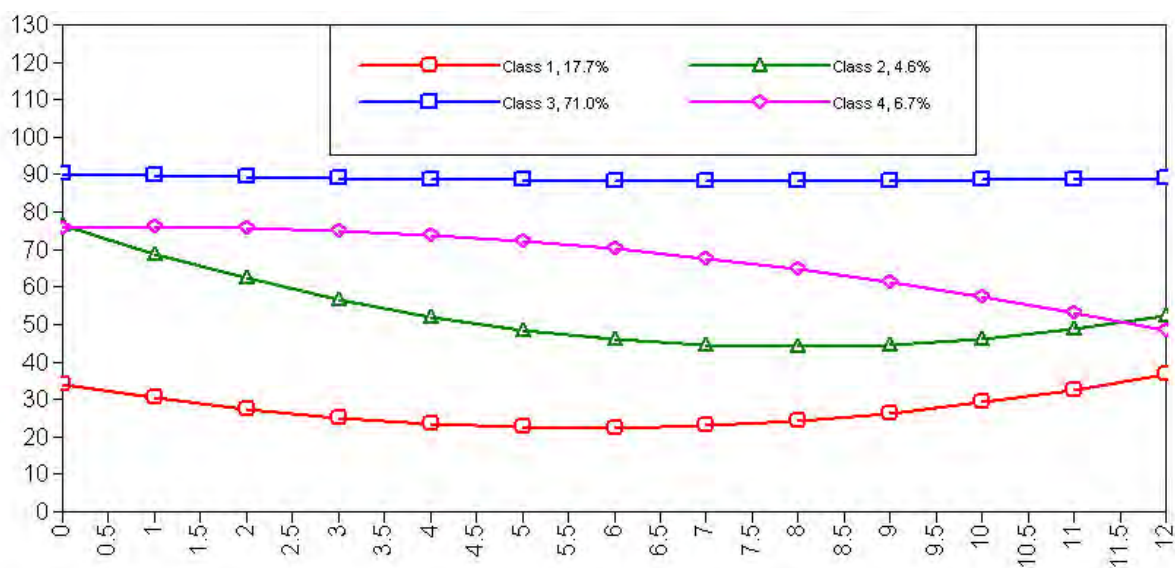
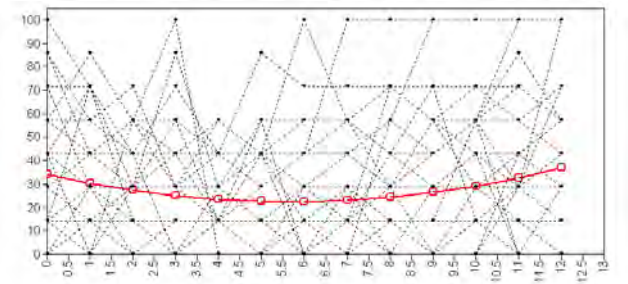
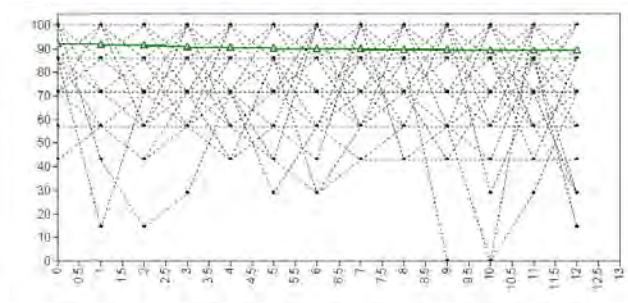


Figure 4.8. Estimated Means for Trajectories of Change of the 4-Class Model with Covariates.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data. Class 1 = LFC, Class 2 = FC, Class 3 = HFC, Class 4 = DC.

(a) High Functioning Clients (HFC)

(b) Low Functioning Clients (LFC)



(c) Deteriorating Clients (DC)

(d) Fluctuating Clients (FC)

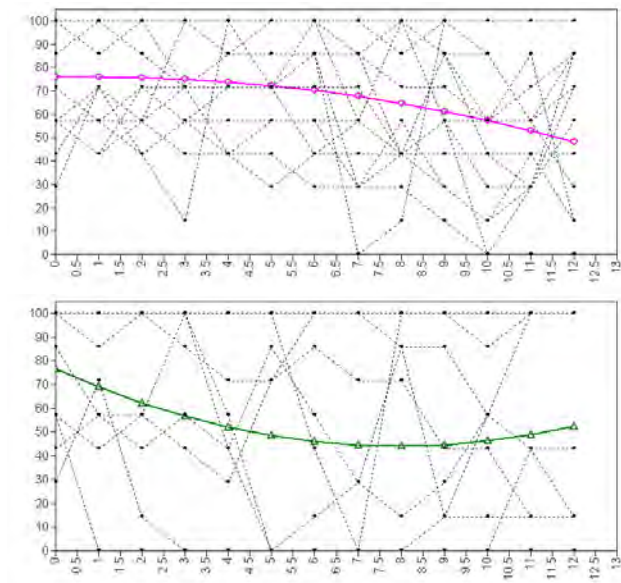


Figure 4.9. Estimated Means and Observed Individual Values for HFC, LFC, DC, and FC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Tables 4.7 to 4.10 represent the parameters of the GMM for each class. Similar to the two-class model, HFC individuals who chose an abstinence goal at intake finished treatment with a significantly higher percentage of functional days than those who chose a moderation goal ($\beta_0 = -10.49$, $p < .001$). The estimated mean of percentage of functional days at post-treatment for HFC who chose abstinence was 96.79%, whereas for individuals who chose moderation it was 89.36%. This relationship was stable across time since neither the linear nor the quadratic slopes were significant ($\beta_1 = -0.30$, $p = .58$;

$\beta_2 = 0.06, p = .33$). Forty individuals with an abstinence goal versus 103 individuals with a moderation goal were classified as HFC. Regarding pretreatment drinking, HFC who finished treatment with lower functional days had a significantly higher number of days drinking 5 or more drinks than those who had a higher percentage of functional days prior to entering treatment ($\beta_0 = -0.14, p = .001$). Estimated means of follow-up functional days for individuals with a higher number of days consumed 5 or more drinks pretreatment was 85.71% versus 94.29% for individuals with a lower number of days consumed 5 or more drinks pretreatment. As with goal choice, this relationship was stable across time ($\beta_1 = -0.02, p = .08; \beta_2 = 0.00, p = .08$).

Goal choice also showed significant results within LFC for all of the growth factors ($\beta_0 = 29.48, p < .001; \beta_1 = 7.23, p < .001; \beta_2 = 0.42, p < .001$). Five individuals with an abstinence goal versus 29 individuals with a moderation goal were classified as LFC. The significance of the growth factors indicates differences observed in shape of the trajectories, such that individuals who chose moderation tend to have a more stable trajectory than individuals who chose abstinence (see Figure 4.10).

Within FC, the growth factors for all covariates were statistically significant with the exception of the intercept for treatment modality and number of days consumed 5 or more drinks pretreatment ($\beta_0 = -17.49, p = 0.06; \beta_0 = 0.22, p = 0.17$). Due to the small sample size ($n = 9$), from these results the only reasonable conclusion is that the significance of the growth factors suggest a high level of variability within individuals in this group (see Figure 4.11 to Figure 4.13). Within the DC group, goal choice also showed significant results for all of the growth factors ($\beta_0 = -53.33, p < .001; \beta_1 = 16.83, p < .001; \beta_2 = -1.36, p < .001$; Figure 4.14). Two individuals with an abstinence goal

versus 12 individuals with a moderation goal were classified as DC. The significance of the growth factors indicates differences observed in shape of the trajectories where individuals who chose moderation tended to have a more stable trajectory than individuals who chose abstinence (see Figure 4.14), but again the sample is very small. Finally, individuals who had more instances where they consumed 5 or more drinks per occasion prior to entering treatment also demonstrated more variability after treatment ($\beta_1 = -0.23, p < .001$; $\beta_2 = 0.02, p < .001$; See Figure 4.15). As with FC, due to the small sample size ($n = 14$), the significance of the growth factors suggests there was high level of variability within individuals in this group.

Table 4.11 shows the odds ratio for the covariates' effects on class membership. Individuals with lower alcohol-related consequences at baseline and lower number of days where they consumed five or more drinks pretreatment had a better chance of being classified as HFC than as LFC and DC. These results are in the same direction as for the two-class model.

Table 4.7

Parameter Estimates for Growth Factors Regressed on Covariates for the High Functioning Clients (HFC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	3.44	-0.88	0.05
Goal Choice	-10.49**	-0.30	0.06
Number of Consequences	0.48	-0.09	0.00
Number of days consumed 5 or more drinks per day	-0.14*	-0.02	0.00

** $p < .001$; * $p < .05$

Table 4.8

Parameter Estimates for Growth Factors Regressed on Covariates for Low Functioning Clients (LFC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	-2.02	-0.67	-0.08
Goal Choice	29.48*	-7.23*	0.42*
Number of Consequences	0.58	0.72	-0.01
Number of days consumed 5 or more drinks per day	-0.33	0.01	0.00

* $p < .001$

Table 4.9

Parameter Estimates for Growth Factors Regressed on Covariates for the Fluctuating Clients (FC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	-17.49	8.91**	-0.66**
Goal Choice	-19.14***	17.04***	-1.24***
Number of Consequences	19.33***	-2.00**	-0.16**
Number of days consumed 5 or more drinks per day	0.22	-0.36***	0.03***

*** $p < .001$, ** $p < .05$

Table 4.10

Parameter Estimates for Growth Factors Regressed on Covariates for Deteriorating clients (DC)

Covariates	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
Modality	-9.97	3.28	-0.08
Goal Choice	-53.33*	16.83*	-1.36*
Number of Consequences	-6.39	1.10	-0.04
Number of days consumed 5 or more drinks per day	0.26	-0.23*	0.02*

** $p < .001$

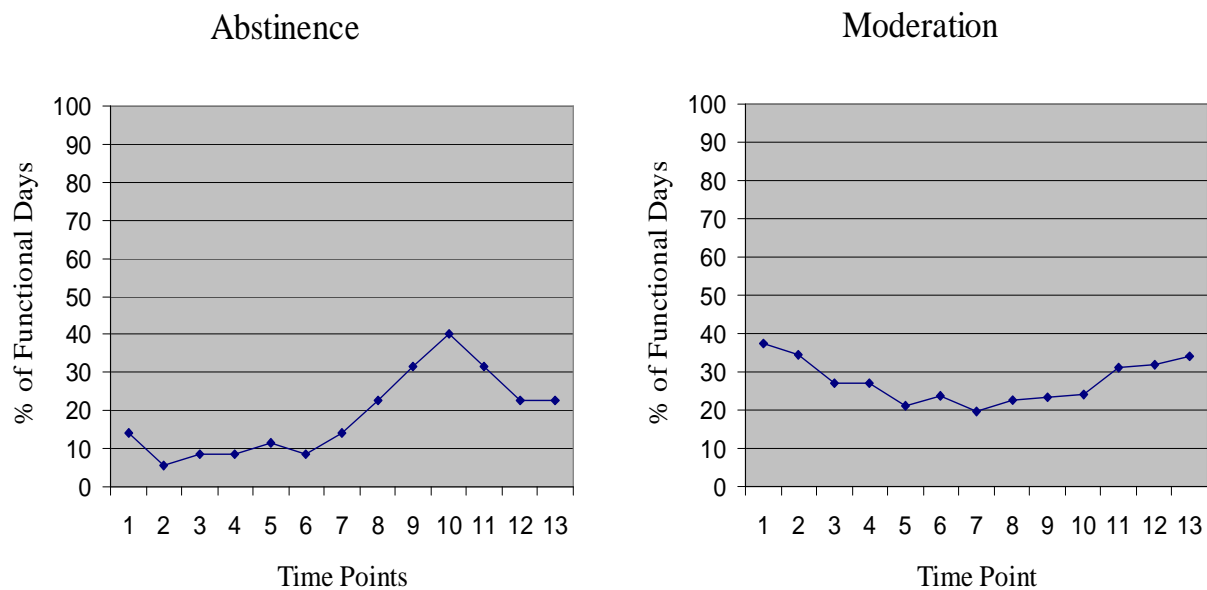


Figure 4.10. Estimated Mean Comparison for Goal Choice among LFC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

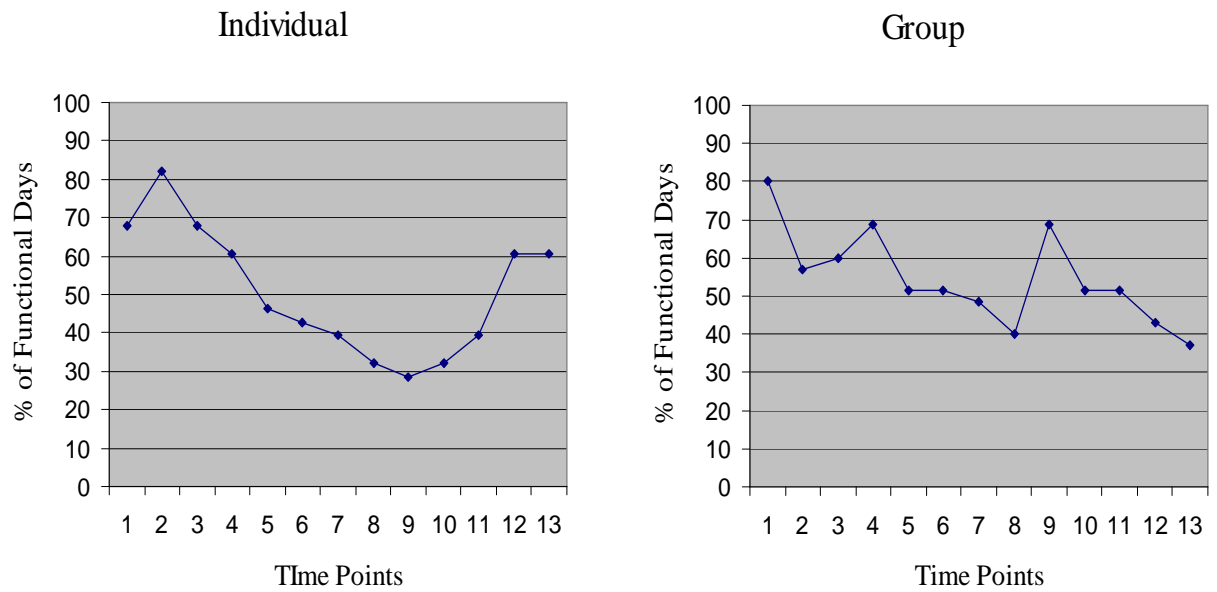


Figure 4.11. Estimated Mean Comparison for Treatment Modality among FC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

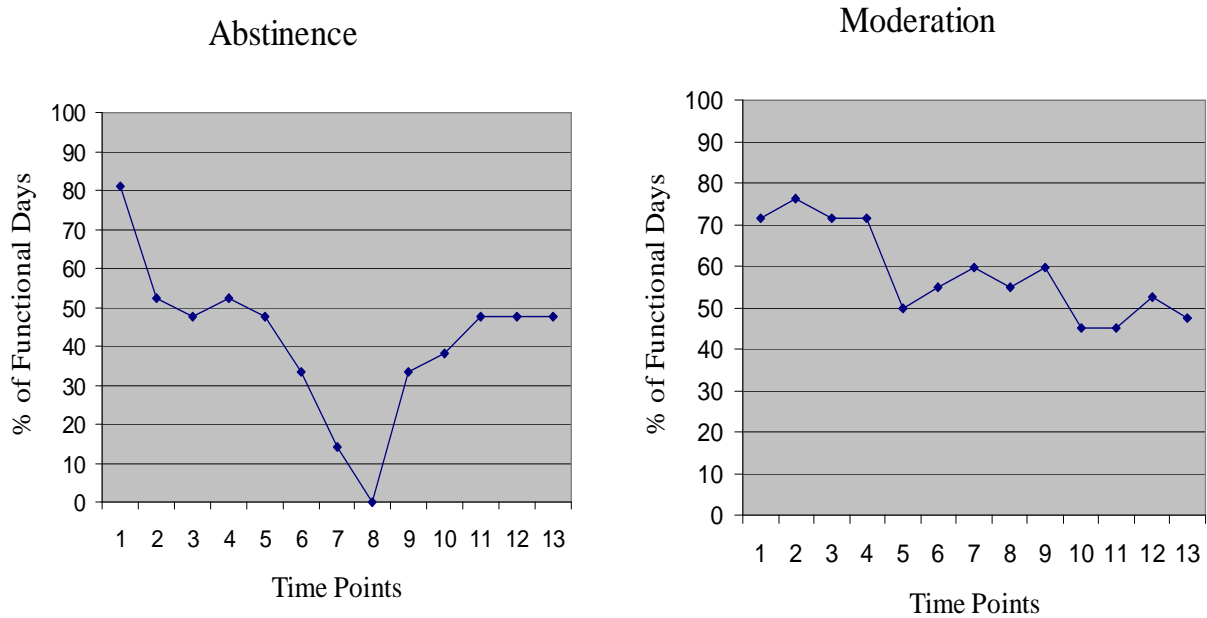


Figure 4.12. Estimated Mean Comparison for Goal Choice Among FC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

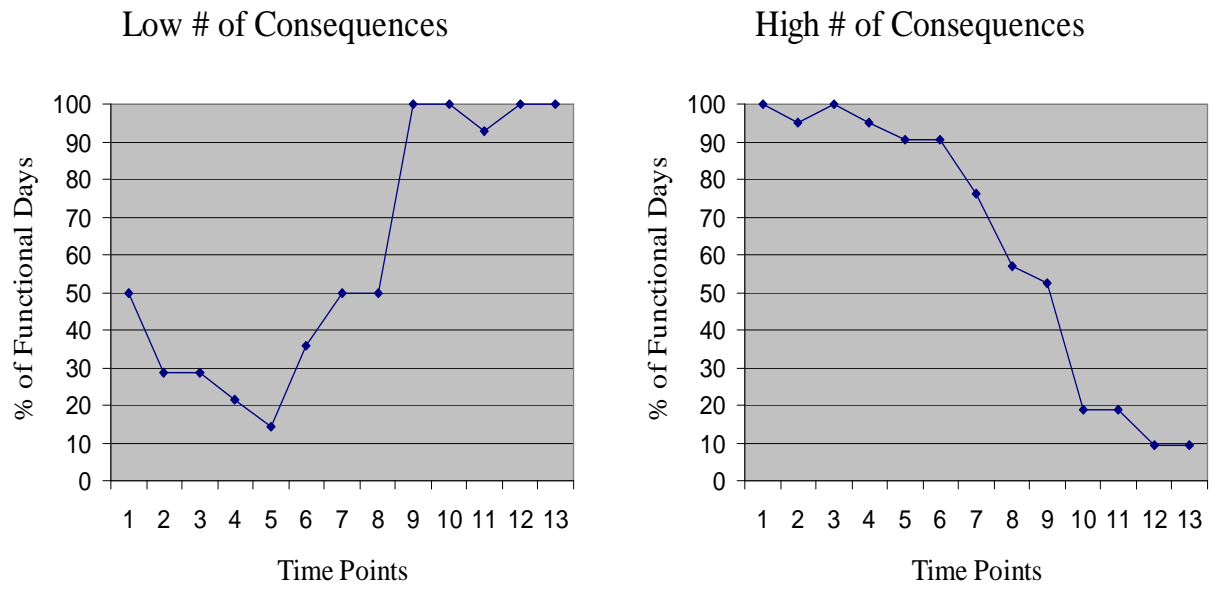


Figure 4.13. Estimated Mean Comparison for Number of Alcohol-Related Consequences Among FC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

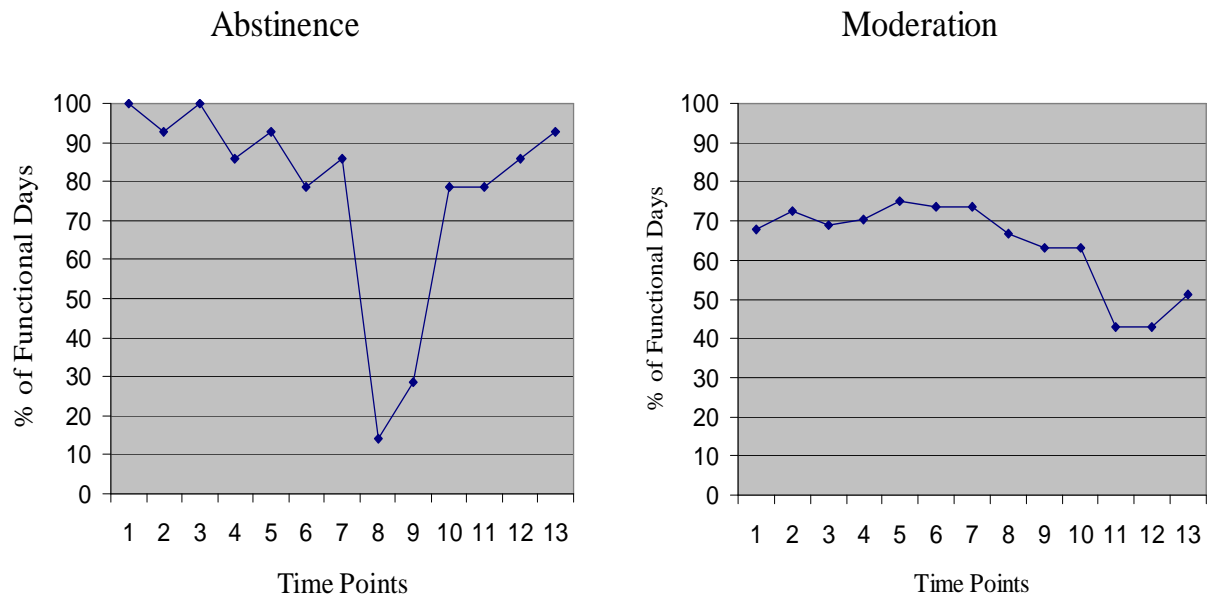


Figure 4.14. Estimated Mean Comparison for Goal Choice Among DC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

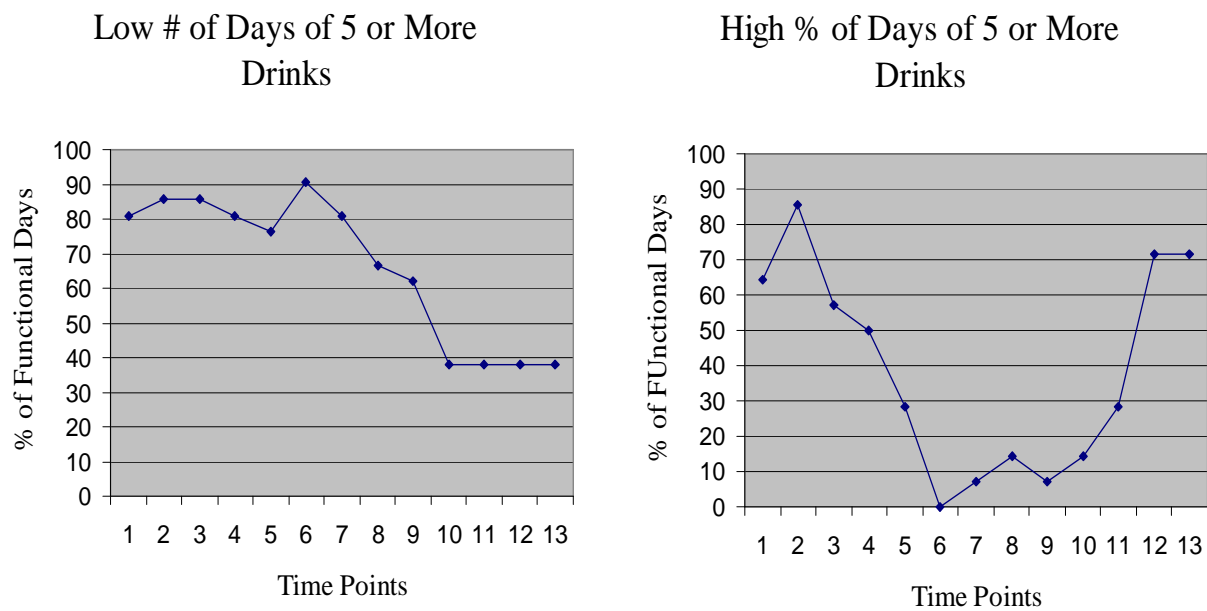


Figure 4.15. Estimated Mean Comparison for Days consumed 5 or more Drinks Among DC.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of TLFB data.

Table 4.11

Odds Ratio (95% confident intervals) for Comparisons between Four-Trajectory

Covariates	OR(95% CI) - HFC	OR(95% CI)- LFC	OR(95% CI) - DC
<i>Low-Functioning Clients (LFC)</i>			
Modality	1.13 (0.51–2.53)	--	--
Goal Choice	2.45 (0.85–7.04)	--	--
Number of Consequences	0.79 (0.63–0.99)**	--	--
Number of days consumed 5 or more drinks per day	0.98 (0.97–0.99)**	--	--
<i>Deteriorating Clients (DC)</i>			
Modality	2.12 (.61–7.45)	0.42 (0.02–1.60)	--
Goal Choice	0.45 (0.09–2.26)	0.91 (0.15–5.50)	--
Number of Consequences	1.74 (1.20–2.53)**	0.73 (0.49–1.08)	--
Number of days consumed 5 or more drinks per day	1.03 (1.01–1.05)*	0.99 (0.97–1.02)	--
<i>Fluctuating Clients (FC)</i>			
Modality	.91 (0.23–3.63)	1.03 (0.23–4.67)	0.43 (.07–2.53)
Goal Choice	1.25 (0.29–5.37)	3.07 (0.57–16.65)	2.79 (0.35–22.15)
Number of Consequences	1.35 (0.91– 2.01)	1.07 (0.70–1.64)	0.78 (0.46–1.30)
Number of days consumed 5 or more drinks per day	1.01 (0.99–1.03)	0.99 (0.96–1.01)	0.98 (0.96–1.01)

Note: ^aClass reference HFC; ^bClass reference DC; ^cClass reference LFC

** $p < .05$; * $p < .10$

Comparing the Growth Mixture Models With and Without Covariates

The likelihood-ratio chi-square difference test was used to test whether the GMM model with covariates was preferable and created a better fit than the model without the covariates (Satorra, 2000). Table 4.12 shows the indicators and parameters to compute this analysis. The chi-square difference tests showed that for both the two- and four-class model, the models with the covariates were preferable and showed better fits ($8X^2 = 143.33$ and 307.54 , respectively).

Table 4.12

Comparison between Models with and without Covariates

Models	Chi-square	Scaling Correlation Factor	Number of Free Parameters
2-Class	-10955.63	2.460	14
2-Class with Covariates	-10685.088	2.036	54
4-Class	-10860.447	2.491	34
4-Class with Covariates	-10554.014	1.537	94

Growth Mixture Models for TLFB Assessment Data

After examining the individual trajectories of pre-treatment drinking data, three growth factors were used corresponding to the intercept (β_0) and linear (β_1) and quadratic slopes (β_2 ; see Figure 4.1). Each of the growth factors was influenced by the latent class variable. The fit indicators for the one to six-class trajectory models are presented in Table 4.13 and the specific class trajectories are shown in Figure 4.16. According to the

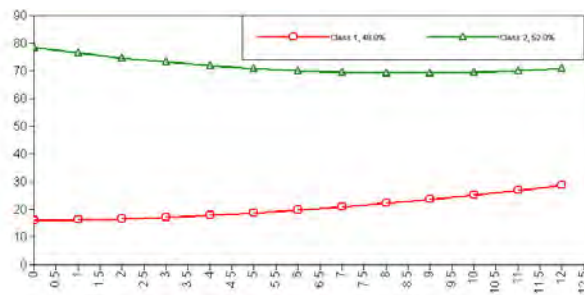
aBIC decrease rate, none of the models captured a significantly different parsimony. The rate of the aBIC difference (Δ aBIC) was generally constant and ranged from 32.32 to 52.63 for the first five models; then the Δ aBIC decreased to 17.25 from the five- to the six-class model. In general, all the models showed high entropy but the four- to the six-class model showed the highest (0.94). Based on the LRT indicator, a 6-class model had the better fit compared to the $k-1$ model. Therefore, according to these indicators, either the two- or the six-class model seemed to produce the best fit. The Δ aBIC indicates that the two-class model is more parsimonious than the six-class model (Δ aBIC = 48.27 and Δ aBIC = 17.25, respectively). However, the entropy for the six-class model is higher than the two-class model (.94 and .85, respectively). In this specific case, a two-class model was chosen for the sequential process GMM analysis since it has a theoretical root. This model represents the idea that there are individuals who come to treatment with different severity levels.

Table 4.13

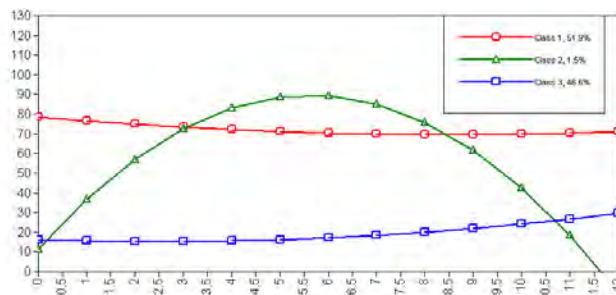
Model Fit for Growth Mixture Models with Assessment TLFB Data

Outcome k-class model	Log-likelihood (# free parameters)	Entropy	aBIC	LRT	BLRT <i>p</i> -value
1-class	-11602.29 (22)	--	23251.77	--	--
2-class	-11573.87 (26)	0.85	23203.50	54.28, <i>p</i> = .21	56.84, <i>p</i> < .0005
3-class	-11553.42 (30)	0.91	23171.18	36.04, <i>p</i> = .29	37.73, <i>p</i> < .0005
4-class	-11522.81 (34)	0.94	23118.55	52.38, <i>p</i> = .10	54.85, <i>p</i> < .0005
5-class	-11492.86 (38)	0.94	23067.22	57.22, <i>p</i> = .15	59.91, <i>p</i> < .0005
6-class	-11479.93 (42)	0.91	23049.97	62.23, <i>p</i> = .04	65.16, <i>p</i> < .0005

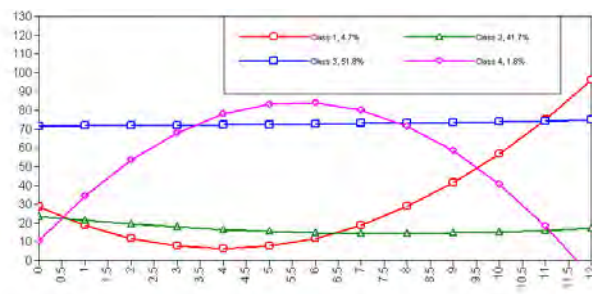
(a) 2-Class Model



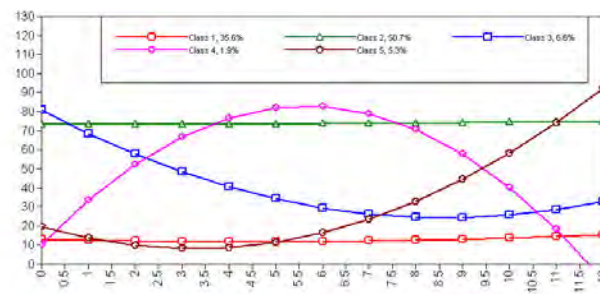
(b) 3-Class Model



(c) 4-Class Model



(d) 5-Class Model



(e) 6-Class Model

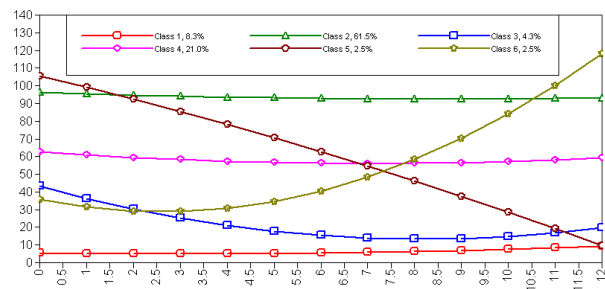


Figure 4.16. Pre-Morbid Alcohol Trajectories for the 2-Class to the 6-Class Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of pretreatment TLFB data.

Two-Class Model for Pre-Treatment Drinking Trajectories

As seen in Figure 4.17, the classes in the two-class model can be described as the low drinking severity group (LSG; n = 104, 52%) and the high severity drinking group

(HSG; $n = 95$, 47%). Estimated means and individual observed values for each category can be seen in Figure 4.18. Participants in the LSG category are characterized by tending to function well for most days in the weeks leading up to treatment (estimated means range from 66.50 to 78.13; see Figure 4.18a). Individuals in the HSG group are characterized as reporting only a small percentage of functional days before entering treatment (estimated means range from 15.40 to 33.74; see Figure 4.18b). It is also obvious in Figure 4.18 that there is a great deal of pretreatment weekly variation among members of both classes. Table 4.14 presents the parameters of the GMM for each class. In the HSG, the intercept is significant, but neither the linear nor quadratic slopes were significant ($\beta_1 = 0.2$, $p = .83$; $\beta_2 = 0.07$, $p = .37$), meaning that there was not a statistically significant level of variation within the three months prior to treatment. In contrast, in the LSG group, both slopes were statistically significant ($\beta_1 = -2.18$, $p = .002$; $\beta_2 = .13$, $p = .02$), thus indicating individuals' variability before treatment.

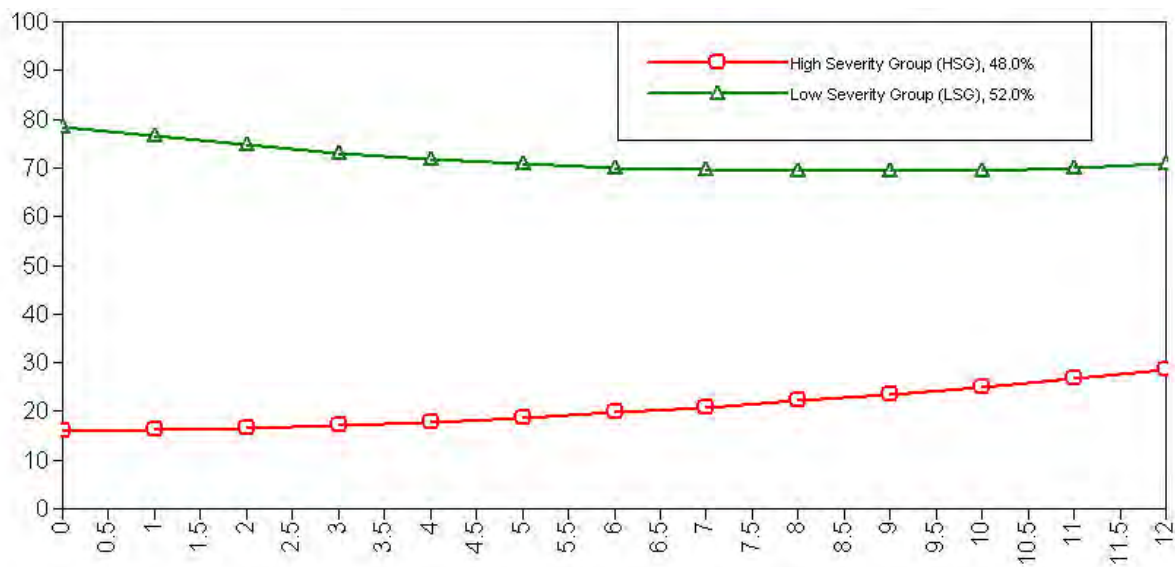


Figure 4.17. Estimated Means for the Pre-morbid Drinking Trajectories of the 2-Class Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of pretreatment TLFB data.

(a) Low Severity Group – LSG

(b) High Severity Group – HSG

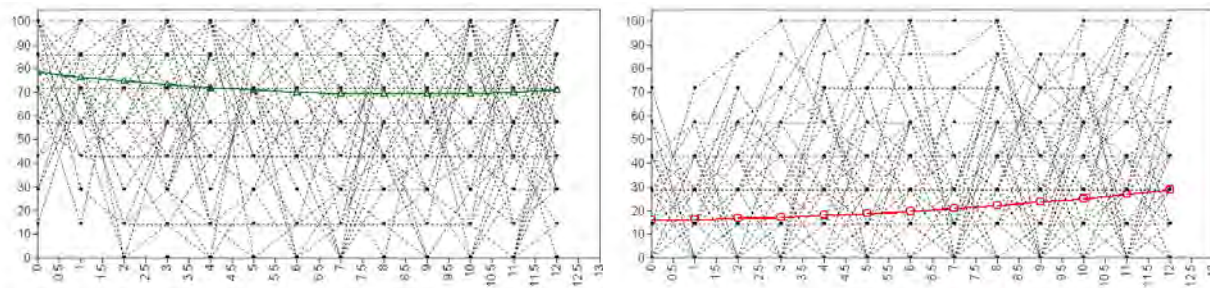


Figure 4.18. Estimated Means and Observed Individual Values for the LSG and the HSG.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of pretreatment TLFB data.

Table 4.14

Growth Factor Means for Each Drinking Class for the Two-Class Model for the Pre-morbid Alcohol Trajectories

Drinking Classes	Rate of Change		
	Intercept (β_0)	Linear Slope (β_1)	Quadratic Slope (β_2)
High Severity Group (HSG)	15.91**	0.2	0.07
Low Severity (LSG)	78.48**	-2.18*	0.13*

** $p < .001$; * $p < .05$

Sequential Process Growth Mixture Model

Since the two-class model for both the pre-treatment and follow-up data showed the best balance between parsimony and fit, these models were used for the sequential process GMM (see Figure 4.19 and Figure 4.20). The classifications of clients into each drinking class according to posterior probability can be seen in Table 4.15. The posterior probabilities revealed that approximately 65% of the participants in the LSG tended to improve and reach a high number of functional days during follow-up with a stable change rate occurring after treatment ($\beta_{12} = -0.58$, $p = .06$; $\beta_{22} = 0.01$, $p = 0.86$; see Figure 4.21a and Table 4.13). As shown in Table 4.16, individuals in the LSG had a .77 probability of having a high percentage of functional days during follow-up. In this class, percentage of functional days ranged from 54.61 to 59.98 before treatment and 86.94 to 95.62 after treatment (see Figure 4.21a). The remaining individuals in the LSG (19%) were classified as LFC (range = 53.93 to 62.23; see Figure 4.21b). These individuals

tended to be the ones among the LSG with lower functional days (range = 25.65 to 36.47) at intake. Even though these individuals were classified as LFC, they increased their functional days at follow-up compared to their baseline alcohol severity level (see Figure 4.21b). As with the HFC, their change during follow-up appeared to be stable across time ($\beta_{12} = 1.28, p = .47; \beta_{22} = -0.10, p = 0.41$; see Figure 4.21b).

Regarding HSG, most of these individuals were classified as LFC (69%; see Figure 4.21c). This class seemed to fluctuate over time, during both the pre-treatment and follow-up time periods ($\beta_{21} = -0.18, p = .04; \beta_{22} = 0.21, p = .02$; see Figure 4.21b and Table 4.17). Clients in this group had overall low functional days before and after treatment (range of estimated means = 10.30 to 32.22 and 4.69 to 21.30, respectively), although the remaining participants (23%) were classified as HFC. Before treatment, their estimated means ranged from 19.18 to 46.97. During follow-up, these individuals showed a variable pattern of functional days ($\beta_{22} = 1.50, p = .01$; range of estimated means = 6.66 to 66.77; see Figure 4.20d and Table 4.17).

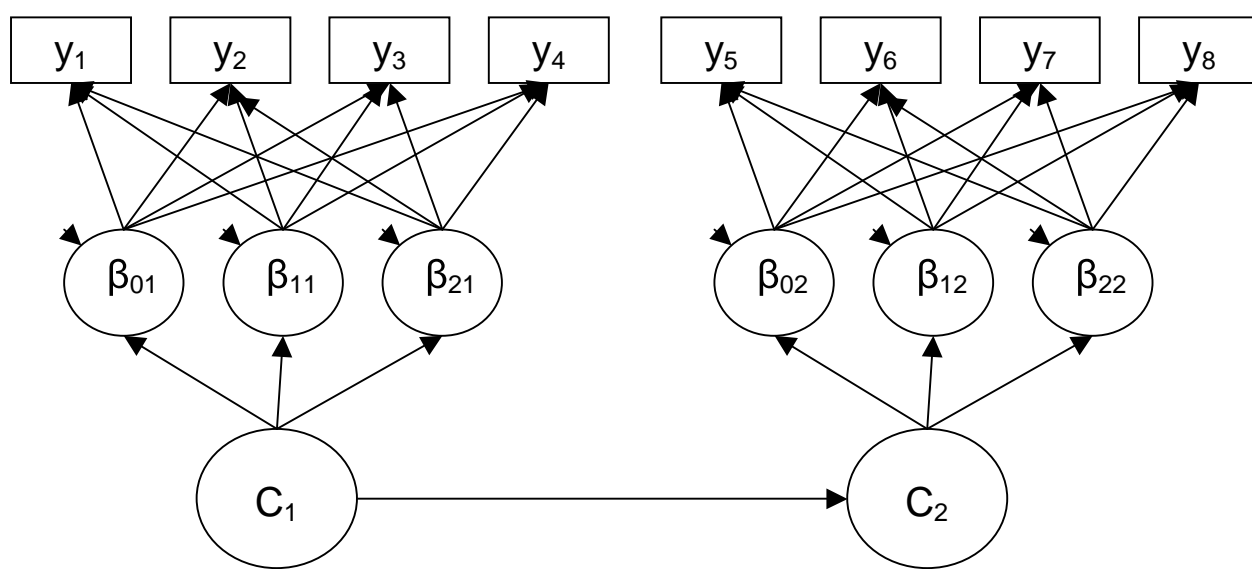


Figure 4.19. Diagram for the Sequential Process GMM Analysis.

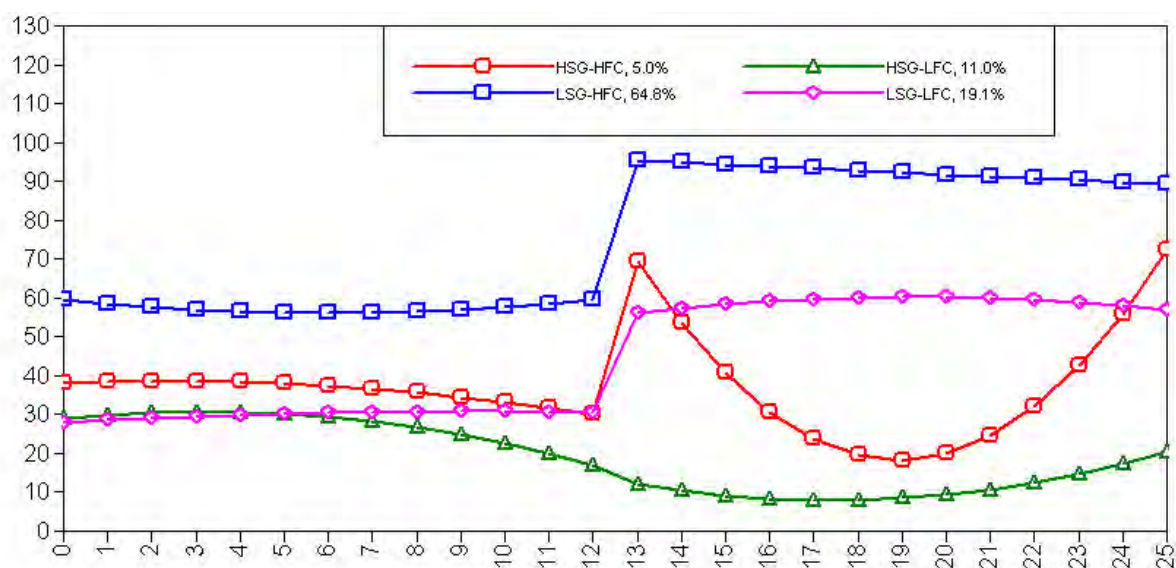


Figure 4.20. Estimated Means for the Change Trajectories of the Sequential Process Growth Mixture Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of pretreatment and post-treatment TLFB data.

Table 4.15

Estimated Posterior Probabilities for a Sequential Process Growth Mixture Model

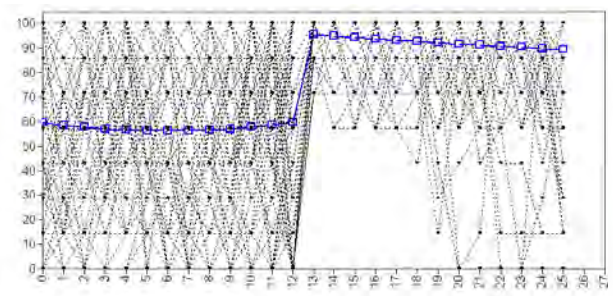
Follow-up	Pre-Treatment		
	LSG	HSG	
HFC	.648	.050	.698
LFC	.191	.109	.300
	.839	.159	~1.00

Table 4.16

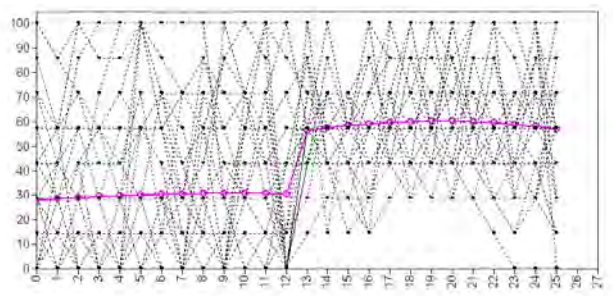
Latent Transition Probabilities for a Sequential Process Growth Mixture Model

Follow-up	Pre-Treatment	
	LSG	HSG
HFC	.77	.23
LFC	.31	.69

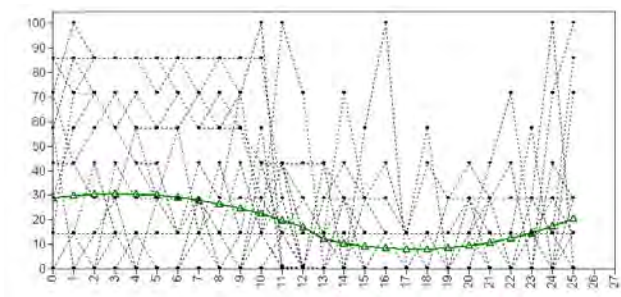
(a) LSG - HFC



(b) LSG - LFC



(c) HSG- LFC



(d) HSG- HFC

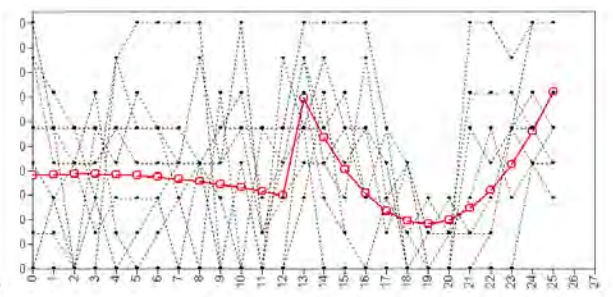


Figure 4.21. Estimated Means and Observed Individual Values the Sequential Process Growth Mixture Model.

Note: the y-axis represents the number of functional days and the x-axis represents the 3 months (12 weeks) of pretreatment and post-treatment TLFB data.

Table 4.17

Growth Factor Means for Each Drinking Class

Drinking Classes	Rate of Change					
	Pre-treatment			Follow-up		
	β_{01}	β_{11}	β_{21}	β_{02}	β_{12}	B_{22}
LSG –HFC	59.57**	-1.13	0.10	95.52**	-0.58	0.01
LSG – LFC	27.88**	0.61	-0.03	56.23**	1.28	-0.10
HSG- HFC	38.16**	0.41	-0.09	69.30**	-17.27**	1.50**
HSG- LFC	28.85**	1.14	-0.18*	12.12**	-1.89	0.21*

** $p < .001$; * $p < .05$

Latent Class Analysis for Alcohol-Related Consequences

Table 4.18 presents the observed sample sizes and the proportion of participants who endorsed each of the eight possible alcohol-related consequences assessed at intake. One- to four-class models were estimated (see Table 4.19) using LCA. Indicators are presented in Table 4.19. The lowest BIC value of the LCA models was for the two-class model (BIC = 1838.21). The non-significant p -value of the BLRT for the 4-class model indicated that the addition of one class to the model did not add any relevance to the model. The BIC increases for the three- and four-class models, indicating less parsimony. Thus, the two-class model was chosen as the best LCA model for these data.

Table 4.18

Observed Sample Size and Proportion for the Eight Binary Alcohol-Related Consequences

Consequences	<i>N</i>	Proportion (%)
Cognitive	138	68.0
Affective	127	62.6
Interpersonal	127	62.6
Financial	95	46.8
Aggressive	91	44.8
Vocational	82	40.4
Health	36	17.7
Legal	4	2.0

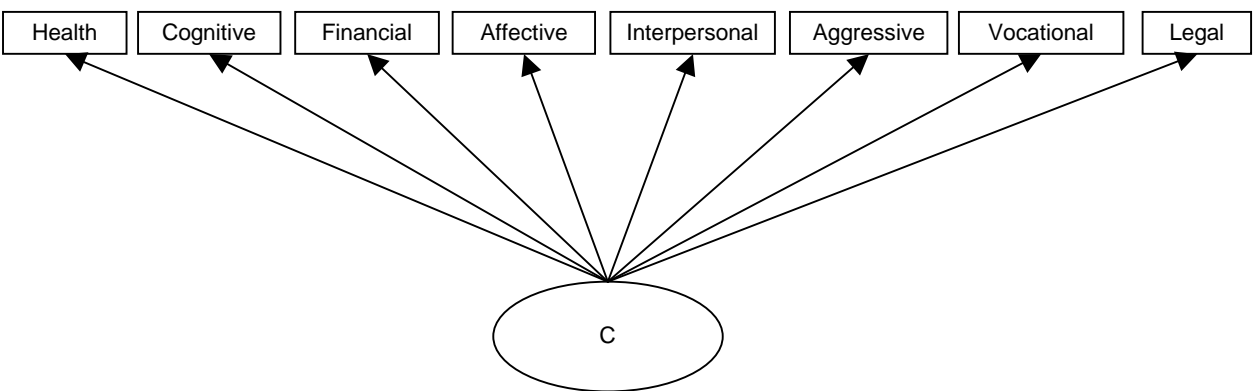


Figure 4.22. Latent Class Analysis Diagram for Alcohol-Related Consequences.

Table 4.19

Model Fit for the Latent Class Analysis

k-class model	Log-likelihood (# parameters)	Entropy	BIC	BLRT p -value
2-class	-868.68 (19)	0.69	1838.21	121.14 $p < .0005$
3-class	-856.07 (29)	0.69	1866.08	25.21, $p < .0005$
4-class	-847.55 (39)	0.83	1902.12	17.05, $p = .31$

The estimated probabilities by item for the two classes are graphically presented in Figure 4.23. The first class, the Less Impacted Group (LIG), contains almost two-thirds (60.6%) of the total sample. The second class, the Impacted Group (IG), contains 39.4% of the sample. Estimated probabilities of endorsing an alcohol-related consequence for individuals within a given class are presented in Table 4.20. Within the LIG, estimated probabilities ranged from 0.02 to 0.54, whereas estimated probabilities in the IG ranged from 0.03 to 0.93. Regarding specific item responses, the estimated probabilities are at least 30% larger in the IG than in the LIG for all consequences except for the health and legal items.

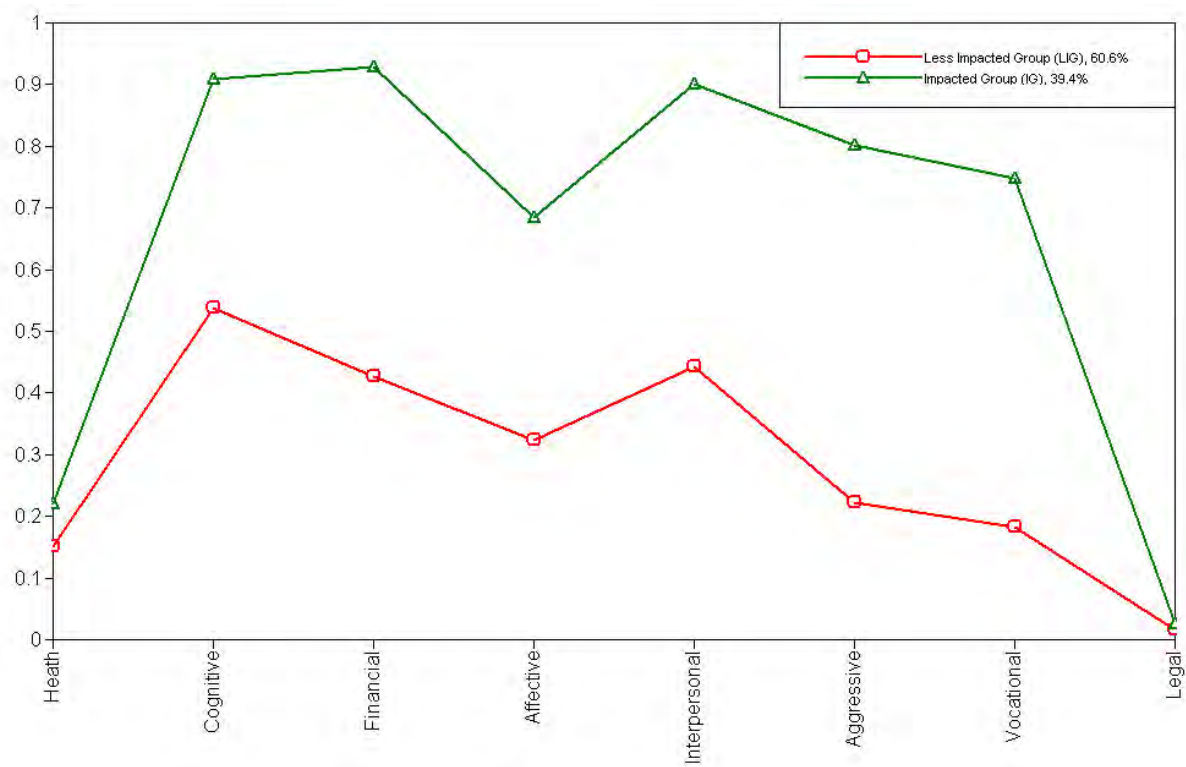


Figure 4.23. Estimated Probabilities of Endorsing a Alcohol-Related Consequence for Each Class.

Table 4.20

Estimated Probabilities for the 2-Class LCA Solution

Alcohol consequences	Classes	
	Less Impacted Group (LIG)	Impacted Group (IG)
Health	0.15	0.22
Cognitive	0.54	0.91
Financial	0.43	0.93
Affective	0.32	0.69
Interpersonal	0.44	0.90
Aggressive	0.22	0.80
Vocational	0.18	0.75
Legal	0.02	0.03

Cross-Tabulation Chi-square Analysis

As shown in Table 4.21, the latent classes obtained by the LCA for alcohol-related consequences and by the GMM for alcohol consumption for the 3 months after treatment were not related (Chi-square = 0.02, $p = .89$). A similar percentage of individuals classified in the LIG and the IG classes were clustered as HFC (80% and 80.8%, respectively), indicating that neither the LIG nor the IG classes tended to classify

individuals in a particular class during follow-up. In addition, a point-biserial correlation between the estimated class probabilities for the classes in the model was not significant ($r = 0.007, p = .93$).

Table 4.21

Cross-Tabulation Analysis for Alcohol-Related Consequences and Functional Days at Follow-up

Pre-treatment Classes		Follow-up Classes		Total
		LFC	HFC	
LIG		24	99	123
	% within Pre-treatment	20.0%	80.0%	100%
	% within Follow-up	62.5%	61.3%	61.6%
	% of Total	12.3%	49.3%	61.6%
IG		15	62	77
	% within Pre-treatment	19.2%	80.8%	100%
	% within Follow-up	37.5%	38.7%	38.4%
	% of Total	7.4%	31.0%	38.4%
Total		39	161	200
	% within Pre-treatment	19.7%	80.3%	100%
	% within Follow-up	100%	100%	100%
	% of Total	19.7%	80.3%	100%

CHAPTER V:

Discussion

Drinking Trajectories During Follow-Up

This study evaluated whether a person-centered approach was able to identify different change patterns among problem drinkers who had completed a short, outpatient intervention. The first hypothesis was confirmed. Two reliable patterns of drinking

trajectories – high functioning clients (HFC) and low functioning clients (LFC) – were obtained from the early (3 months) post-treatment drinking data. The majority of individuals were classified as HFC, indicating that most participants improved after treatment. These results were similar to what Sobell, Sobell and Agrawal (in press) found using of a variable-centered approach. They found that most individuals who completed the GSC treatment, either in a group or individual format, reduced or stopped their drinking and maintained the change over time.

Additionally, three other classes readily explained by existing theories were identified. The four classes were the fluctuating clients (FC), delayed-change clients (DDC), and deteriorating clients (DC), representing a small percentage of the total sample. The FC involved individuals whose early follow-up trajectory was characterized by abrupt fluctuations between weeks. The DDC did not do well immediately after treatment but improved significantly over the short follow-up. Once covariates were included in the four-class model, a new class was formed called deteriorating clients (DC). Clients in this category displayed a high mean percentage of functional days after treatment, which decreased over time. These results suggest that a person-centered approach captures three types of trajectories: people who improve after treatment (HFC), people who do not change (LFC), and people with different fluctuating patterns after follow-up (e.g. FC, DDC, DC). The separate evaluation of the different fluctuating pattern categories should be considered tentative as the trajectories of change were examined over a relatively short time period. Since the categories changed when the covariates were incorporated into the model, the covariates seem to have an important

role in classifying these individuals and assigning meaningful interpretations to the different change patterns.

Relationship of Pretreatment Variables to Drinking Trajectories at Follow-up

Another objective of this study was to assess the extent to which pretreatment covariates were able to differentiate between different patterns of early outcomes. The goal was to examine whether a person-centered statistical approach provides valuable information for the identification of outcome predictors. The second hypothesis which posited that alcohol-related consequences, pre-morbid drinking patterns, goal choice, and treatment modality would be related to treatment outcomes was partially confirmed. The effects of the covariates were assessed by incorporating them into the two- and four-class latent models. Additionally, analyses of the relationship of drinking levels to groups were investigated by examining class transitions between the baseline alcohol latent trajectories and latent classes based on alcohol-related consequences and the drinking latent classes at post-treatment.

In both the two- and the four-class model, goal choice was related to treatment outcome, but only for the high functioning outcome group. High functioning individuals who chose an abstinence goal at intake had a somewhat higher percentage of functional days than those who chose a moderation goal, although both subgroups had a very high mean percentage of functional days. This relationship was stable throughout the 3-month follow-up. It is important to consider this finding in context, however. First, the number of individuals who chose abstinence were a minority ($n = 42$; 31.6%) among HFC.

Second, this relationship was not sustained in the multinomial logistic regression of class membership. Third, the choice of a moderation goal was not manipulated but rather was self-selected, and thus it could reflect the influence of multiple variables not measured in the study. Fourth, this study only examined a three-month follow-up period, when results are less likely to be stable. Finally, the pursuit of low-risk drinking is likely to involve some trial and error, which could be reflected in early outcomes. The present results are not consistent with the scant literature on goal choice among problem drinkers (Booth et al., 1984; Booth et al., 1992; Ojehagen & Berglund, 1989; Sanchez-Craig et al., 1984), which shows a lack of relationship between goals and outcomes, but that literature involves aggregated outcomes over much longer intervals (e.g., two years).

The number of alcohol-related consequences also was associated with the latent classes in the two- and four-class models. In the two-class model, members of the HFC class, who endorsed a lower number of consequences at intake, experienced more functional days during the follow-up period. Among LFC, this relationship was inverted in that individuals with more alcohol consequences at intake displayed more functional days after treatment. This last finding requires cautious interpretation since the sample size was small ($n = 22$). In the four-class model, individuals with a lower number of alcohol-related consequences at pretreatment had a higher chance of being classified as HFC than as LFC or DC.

In contrast to the findings obtained for the GMMs with covariates, no relationships were found between the latent classes obtained for alcohol-related consequences at intake and those based on the level of alcohol consumption after treatment. According to the LCA, the two classes obtained from alcohol-related

consequences were the impacted group (IG) and the less impacted group (LIG). Group membership was not associated with number of functional days after treatment. These findings indicate that the relationship between alcohol-related consequences and treatment outcomes depends on how this variable is manipulated in the analyses. Significant findings associated with treatment outcomes were found when alcohol-related consequences was used as an interval variable (number of alcohol-related consequences), whereas a categorical analysis of alcohol-related consequences using a LCA model did not provide significant results on treatment outcomes. Other studies that have examined alcohol-related consequences and analyzed the effect of independent consequences supported the idea that alcohol-related consequences are associated with treatment outcomes (i.e. Gordon & Zrull, 1991; John et al., 2003; Marlatt & Gordon, 1985). The fact that the error variance was not taken into account in the classification analysis could explain the lack of significant results in the LCA. Another possible reason is that this sample did not include individuals with higher levels of drinking problem severity.

Regarding baseline alcohol severity levels, in both the two- and the four-class model, HFC who had fewer days of consuming five or more drinks at baseline had more functional days during follow-up. In the two-class model, having more days where five or more drinks were consumed was associated with fluctuation of drinking patterns after treatment within the HFC class. Interestingly, class membership was associated with number of days consuming five or more drinks. High functioning clients had a lower number of days consuming five or more drinks at baseline than LFC for both the two- and four-class model, and DC for the four-class model. This relationship was confirmed in the sequential process GMM analysis. Here, a latent growth mixture analysis was used

as an innovative tool to classify drinking patterns based on assessment data. This analysis produced the low severity group (LSG) and the high severity group (HSG). These latent classes were associated with the two-class model obtained using the follow-up data. Findings from this analysis revealed that individuals who started treatment with lower severity levels had more than a 75% chance of being classified as HFC after treatment, whereas participants with higher severity levels at intake tended to have almost a 70% chance of being classified as LFC after treatment. These results support the idea that alcohol problem severity levels are related to treatment outcomes (Hesselbrock et al., 1987; Witkiewitz, 2008; Witkiewitz et al., 2007).

In relation to treatment format, it is important to highlight that similar to the results obtained by Sobell et al. (in press), the covariate effect of treatment modality was not significant and was not related to class membership. This finding is consistent with studies comparing treatment efficacy of MI or CBT in individual and group formats (Graham et al., 1996; Marques & Formigoni, 2001; Weiss et al., 2004).

Significance of the Study

The results from these analyses support the notion that problem drinkers do not constitute a homogeneous population, neither before nor after treatment. That is, problem drinkers can be classified into meaningful subgroups. Identification of such subgroups can assist in understanding the nature of alcohol problems, and it can also serve to generate client-treatment matching hypotheses. Beginning in the 1990s, more complex statistical techniques became available allowing for the testing of models that better represent the complex relationships involved in behavioral changes. Growth mixture modeling is one such technique for studying the complexity of the change process. This

model combines the general latent variable modeling framework with multivariate design, resulting in a flexible approach to analyzing longitudinal data in the social sciences (Hix-Small, Duncan, Duncan, & Okut, 2004). Thus, growth mixture modeling gives researchers the opportunity to explore and test complex theories that have not been statistically evaluated due to limitations of traditional statistical techniques. Such new statistical techniques can benefit researchers in examining the complexities of the phenomena and mechanisms that interact to affect human behavior. In the alcohol field, due to the high relapse rate following treatment, it is important to explore the individual differences and risk factors related to relapse rates and the individual's change process. This information can potentially suggest treatment strategies that could be evaluated in clinical trials.

Three major findings provide evidence of the value of using a person-centered approach in the evaluation of treatment outcomes. First, even though problem drinkers seem to constitute a homogeneous population, the significant differences observed among the classes in terms of frequency of alcohol use, and variability in change patterns demonstrates the feasibility of examining drinking data in aggregated subgroups in order to further understand the specific relationships between variables and outcomes. Second, the fact that covariates, such as alcohol severity levels, were significantly associated with the trajectories not only between classes, but also within classes illustrates the importance of examining these variables in a latent class framework. Third, the significant fluctuation observed among individuals demonstrates the importance of considering this factor in the evaluation of treatment outcomes. Related to this, trajectories of change varied according to the covariates introduced in the model, suggesting that introducing different covariates

may help understand the fluctuation patterns. The importance of considering fluctuation was particularly apparent in the sequential process GMM analysis. In that analysis, even though a percentage of individuals in the HSG class were classified as HFC due to the average of functional days across weeks, their progress showed major fluctuations after treatment.

The present study demonstrated that a person-centered analysis can be an effective statistical technique to advance knowledge about variables related to treatment outcomes. Information about the clustering of variables can help create client-treatment matching hypotheses and predict cases (i.e., subgroups) unlikely to improve with certain interventions. Innovated interventions could then be developed for such cases and evaluated to see if they can improve treatment efficacy. Finally, recent studies have successfully found significant results in the use latent class analyses to validate client-treatment matching hypotheses that failed to be validated by conventional statistical techniques (Witkiewitz et al., 2007; Wu & Witkiewitz, 2008).

Limitations

This study has several limitations related to methodological issues and statistical analysis. The follow-up time period and the sample size of the population are two significant limitations. Even though individuals completed a 12-month TLFB, only data from the first 3-months after treatment were used in these analyses to reduce the complexity of the model and to accommodate for the size of the sample. Therefore, results concerning the effect of covariates over time, such as goal choice, should be considered inconclusive. Additionally, due to the small number of individuals classified

in some groups, such as DDC, FC, and DC, the directionality of the significant effect of covariates was not interpretable.

Regarding the limitations of GMMs, since these techniques are fairly new, little is known about requirements in relation to the necessary sample size and the number of time points needed in order to achieve a good estimation with strong power (Muthén, 2004). A considerable limitation is the fundamental idea of the existence of a heterogeneous population, containing relatively homogenous subgroups, which entails different drinking distributions. These models provide an approximation of the mixture distributions of the data (Cudeck & Henly, 2003). Therefore, in mixture models it is difficult to know with certainty which are the exact underlying distributions and if they are reliable among all samples of alcohol users. Thus, the present results need to be interpreted with caution and should not yet be generalized to other populations (Bauer & Curran, 2004). They should be considered exploratory and in need of replication using a different dataset. Since the growth mixture model found in this sample provides a potentially useful representation of the heterogeneous population of problem drinkers after treatment, the utility of this model can be determined by future studies. It is important to note that these results do not suggest that these classes are the only subgroups that can be found among problem drinkers. As was demonstrated, there are many feasible solutions and the selection of the best model depends not only on the statistical indicators, but also on the theory underlying the dataset used and the research question under study.

Future Directions

This study focused on how a person-centered statistical approach can identify predictors of outcomes. This type of study provides clues for hypothesis development for client-matching treatment method and for the application of stepped care treatment strategies. The present findings specifically provided information on drinking trajectories after treatment based on percentage of functional days. As there are many ways of characterizing alcohol use over time, future studies should examine which are the best parameters to use in the estimation of trajectories. More than one drinking variable, such as the number of drinks consumed per drinking day and the percentage of abstinent days can be used for a more complete exploration of latent classes in alcohol abusers. In addition, interactions between covariates, such as goal choice and severity levels, can provide information on patterns of relapse and the dynamics of alcohol abuse after treatment. It will also be important to understand which timeframe is reliable for this type of analysis, as well as which temporal grouping is the best option to capture drinking pattern fluctuations (i.e., days, weeks, months).

Evaluating how this type of statistical technique can aid in understanding the relationship between individual characteristics and outcome results by comparing variable- and person-centered statistical findings can be an objective of future studies. Each method provides a different way of examining a data set, providing information about groups and individuals differences. Using more complex statistical techniques to test relevant hypotheses involved in client-treatment matching can be an objective of future studies.

Future studies should also examine the relationship of within treatment performance as a predictor of outcomes. Strategies such as the stepped-care approach,

which focus on maximizing cost effectiveness, not only consider pre-treatment factors but also initial progress in treatment as aids in determining treatment strategies. Dawes (1994) found that when variables indicating early progress in treatment were entered in the analysis, pre-treatment drinking levels were no longer significant. This suggests that besides selecting the best initial intervention based on pre-treatment variables, clinicians may also obtain relevant information from examining progress in therapy. Therefore, it appears that selecting a criterion based on performance can help clinicians make informed decisions for alcohol abusers who seek treatment (Breslin, Sobell, Sobell, Cunningham, Sdao-Jarvie, & Borsoi, 1999; Sobell & Sobell, 2000). As GMMs provide the opportunity to examine time-variant and time-invariant covariates, the evaluation of both pre- and within-treatment variables as factors in treatment outcomes is possible. Future studies should determine the value of these statistical techniques for strategies that maximize cost-effectiveness of interventions thorough the evaluation of pre- and within-treatment variables.

REFERENCES

- Adamson, S. J., & Sellman, J. D. (2001). Drinking goal selection and treatment outcome in out-patients with mild-moderate alcohol dependence. *Drug and Alcohol Review, 20*(4), 351-359.
- Agosti, V. (1995). The efficacy of treatments in reducing alcohol consumption: A meta-analysis. *International Journal of the Addictions, 30*(8), 1067-1077.
- Agrawal, S., Sobell, L. C., & Sobell, M. B. (2007, in press). The Timeline Followback: A scientifically and clinically useful tool for assessing substance use. In R. F. Belli,

- F. P. Stafford & D. F. Alwin (Eds.), *Using calendar and diary methodologies in life events research*. Beverly Hills, CA: Sage Publications.
- Akerlind, I., Hornquist, J. O., & Bjurulf, P. (1988). Prognosis in alcoholic rehabilitation: the relative significance of social, psychological, and medical factors. *International Journal of the Addictions*, 23(11), 1171-1195.
- Allen, J. P., Litten, R. Z., & Anton, R. (1992). Measures of alcohol consumption in perspective. In R. Z. Litten & J. Allen (Eds.), *Measuring alcohol consumption: Psychosocial and biological methods* (pp. 205-226). Towota, NJ: Humana Press.
- Annis, H. M., & Graham, J. M. (1995). Profile types on the Inventory of Drinking Situations: Implications for relapse prevention counseling. *Psychology of Addictive Behaviors*, 9(3), 176-182.
- Armor, D. J., & Meshkoff, J. E. (1983). Remission among treated and untreated alcoholics. In N. K. Mello (Ed.), *Advances in substance abuse: Behavioral and biological research: Vol. 3* (pp. 239-269). Greenwich, CN: JAI Press.
- Babor, T. F., Cooney, N. L., & Lauerma, R. J. (1987). The dependence syndrome concept as a psychological theory of relapse behaviour: an empirical evaluation of alcoholic and opiate addicts. *British Journal of Addiction*, 82(4), 393-405.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. New Jersey: Prentice Hall, Inc.
- Bauer, D. J., & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods*, 9, 3-29.

- Blume, A. W., Marlatt, G. A., & Schmalings, K. B. (2000). Executive cognitive function and heavy drinking behavior among college students. *Psychology of Addictive Behaviors, 14*(3), 299-302.
- Bollen, K. A. (2006). *Latent Curve Models: A Structure Equation Perspective*. New Jersey: John Wiley & Sons, Inc.
- Booth, B. M., Yates, W. R., Petty, F., & Brown, K. (1991). Patient factors predicting early alcohol-related readmissions for alcoholics: role of alcoholism severity and psychiatric co-morbidity. *Journal of Studies on Alcohol, 52*(1), 37-43.
- Booth, P. G., Dale, B., & Ansari, J. (1984). Problem drinkers' goal choice and treatment outcome: A preliminary study. *Addictive Behaviors, 9*(4), 357-364.
- Booth, P. G., Dale, B., Slade, P. D., & Dewey, M. E. (1992). A follow-up study of problem drinkers offered a goal choice option. *Journal of Studies in Alcohol, 53*(6), 594-600.
- Breslin, F. C., Sobell, M. B., Sobell, L. C., Cunningham, J. A., Sdao-Jarvie, K., & Borsoi, D. (1999). Problem drinkers: Evaluation of a stepped care approach. *Journal of Substance Abuse, 10*, 217-232.
- Brown, S. A., Carrello, P. D., Vik, P. W., & Porter, R. J. (1998). Change in alcohol effect and self-efficacy expectancies during addiction treatment. *Substance Abuse, 19*(4), 155-167.
- Bucholz, K. K., Heath, A. C., Reich, T., Hesselbrock, V. M., Kramer, J. R., Nurnberger, J. I., Jr., et al. (1996). Can we subtype alcoholism? A latent class analysis of data from relatives of alcoholics in a multicenter family study of alcoholism. *Alcoholism: Clinical and Experimental Research, 20*(8), 1462-1471.

- Cahalan, D. (1987). Studying drinking problems rather than alcoholism. In M. Galanter (Ed.), *Recent Developments in Alcoholism*. New York, NY: Plenum.
- Carroll, K. M., Power, M. E. D., Bryant, K., & Rounsaville, B. J. (1993). One-year follow-up status of treatment-seeking cocaine abusers: Psychopathology and dependence severity as predictors of outcome. *Journal of Nervous and Mental Disease*, *181*, 71-79.
- Chang, G., McNamara, T. K., Orav, E. J., & Wilkins-Haug, L. (2006). Brief intervention for prenatal alcohol use: The role of drinking goal selection. *Journal of Substance Abuse Treatment*, *31*(4), 419-424.
- Connors, G. J., Tarbox, A. R., & McLaughlin, E. J. (1986). Contrasting binge and continuous alcoholic drinkers using demographic and drinking history variables. *Alcohol and Alcoholism*, *21*(1), 105-110.
- Corrigan, E. M., & Butler, S. (1991). Irish alcoholic women in treatment: early findings. *The International Journal of Addictions*, *26*(3), 281-292.
- Cronkite, R. C., & Moos, R. H. (1984). Sex and marital status in relation to the treatment and outcome of alcoholic patients. *Sex Roles*, *11*(1-2), 93-112.
- Cudeck, R., & Henly, S. J. (2003). A realistic perspective on pattern representation in growth data: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 378-383.
- Dawes, R. (1994). *House of Cards: Psychology and Psychotherapy Built on Myth*. New York, NY: Free Press.

Dawson, D. A., Grant, B. F., Stinson, F. S., Chou, P. S., Huang, B., & Ruan, W. J.

(2005). Recovery from DSM-IV alcohol dependence: United States, 2001-2002.

Addiction, 100(3), 281-292.

Dies, R. R. (1994). Therapist variables in group psychotherapy research. In A. Fuhriman

& G. M. Burlingame (Eds.), *Handbook of group psychotherapy* (pp. 114-154).

New York: Wiley.

Donovan, D. M., Kadden, R. M., DiClemente, C. C., Carroll, K. M., Longabaugh, R.,

Zweben, A., et al. (1994). Issues in the selection and development of therapies in

alcoholism treatment matching research. *Journal of Studies on Alcohol. Special*

Issue: Alcoholism treatment matching research: Methodological and clinical

approaches. Suppl, 12, 138-148.

Donovan, D. M., Kivlahan, D. R., Kadden, R. M., & Hill, D. (2001). Cognitive

impairment as a client treatment matching hypothesis. In R. Longabaugh & P. W.

Wirtz (Eds.), *Project Match: Hypotheses: Results and Causal Chain Analyses*

(Vol. 8). Washington, DC: NIH Publication.

Duckert, F., Amundsen, A., & Johnsen, J. (1992). What happens to drinking after

therapeutic intervention. *British Journal of Addiction, 87*, 1457-1467.

Edwards, G., Brown, D., Oppenheimer, E., Sheehan, M., Taylor, C., & Duckitt, A.

(1988). Long term outcome for patients with drinking problems: the search for

predictors. *British Journal of Addiction, 83*(8), 917-927.

Epstein, E. E., Kahler, C. W., McCrady, B. S., Lewis, K. D., & Lewis, S. (1995). An

empirical classification of drinking patterns among alcoholics: Binge, episodic,

sporadic, and steady. *Addictive Behaviors, 20*(1), 23-41.

- Epstein, E. E., Labouvie, E., McCrady, B. S., Swingle, J., & Wern, J. (2004). Development and validity of drinking pattern classification: Binge, episodic, sporadic, and steady drinkers in treatment for alcohol problems. *Addictive Behaviors, 29*(9), 1745-1761.
- Fear, N. T., Iverson, A., Meltzer, H., Workman, L., Hull, L., Greenberg, N., et al. (2007). Patterns of drinking in the UK Armed Forces. *Addiction, 102*(11), 1749-1759.
- Foy, D. W., Nunn, L. B., & Rychtarik, R. G. (1984). Broad-spectrum behavioral treatment for chronic alcoholics: Effects of training controlled drinking skills. *Journal of Consulting and Clinical Psychology, 52*(2), 218-230.
- Fuzhong, L., Duncan, T. E., Duncan, S. C., & Hops, H. (2001). Piecewise growth mixture modeling of adolescent alcohol use data. *Structural Equation Modeling, 8*(2), 175-204.
- Gavin, D. R., Ross, H. E., & Skinner, H. A. (1989). Diagnostic validity of the drug abuse screening test in the assessment of the DSM-III drug disorders. *British Journal of Addiction, 84*, 301-307.
- Gordon, A. J., & Zrull, M. (1991). Social networks and recovery: one year after inpatient treatment. *Journal of Substance Abuse Treatment, 8*(3), 143-152.
- Graber, R. A., & Miller, W. R. (1988). Abstinence or controlled drinking goals for problem drinkers: A randomized clinical trial. *Psychology of Addictive Behaviors, 2*, 20-33.
- Graham, K., Annis, H. M., Brett, P. J., & Venesoen, P. (1996). A controlled field trial of group versus individual cognitive-behavioural training for relapse prevention. *Addiction, 91*(8), 1127-1139.

- Heather, N., Brodie, J., Wale, S., Wilkinson, G., Luce, A., Webb, E., et al. (2000). A randomized controlled trial of moderation-oriented cue exposure. *Journal of Studies on Alcohol*, *61*(4), 561-570.
- Heather, N., & Robertson, I. (1981). *Controlled drinking*. London: Muthuen.
- Henson, J. M., Reise, S. P., & Kim, K. H. (2007). Detecting mixtures from structure model differences using latent variable mixture modeling: A comparison of relative model fit statistic. *Structural Equation Modeling*, *14*, 202-226.
- Hesselbrock, V. M., O'Brien, J., Weinstein, M., & Carter-Menendez, N. (1987). Reasons for drinking and alcohol use in young adults at high risk and at low risk for alcoholism. *British Journal of Addiction*, *82*(12), 1335-1339.
- Hix-Small, H., Duncan, T. E., Duncan, S. C., & Okut, H. (2004). A multivariate associative finite growth mixture modeling approach examining adolescent alcohol and marijuana use. *Journal of Psychopathology and Behavioral Assessment*, *26*(4), 255-270.
- Hodgins, D. C., Leigh, G., Milne, R., & Gerrish, R. (1997). Drinking goal selection in behavioral self-management treatment of chronic alcoholics. *Addictive Behavior*, *22*(2), 247-255.
- Jastak, J. F., & Jastak, S. (1965). *The wide range achievement test manual*. Paper presented at the Wilmington, Delaware: Jastak Inc.
- John, U., Veltrup, C., Driessen, M., Wetterling, T., & Dilling, H. (2003). Motivational intervention: An individual counselling vs a group treatment approach for alcohol-dependent in-patients. *Alcohol and Alcoholism*, *38*(3), 263-269.

- Kahler, C. W., Epstein, E. E., & McCrady, B. S. (1995). Loss of control and inability to abstain: the measurement of and the relationship between two constructs in male alcoholics. *Addiction, 90*(8), 1025-1036; discussion 1037-1051.
- Kreuter, F., & Muthén, B. (Draft). Analyzing criminal trajectory profiles: Bridging multilevel and group-based approaches using growth mixture modeling.
- Laird, N. M., & Ware, J. H. (1982). Random-effects models for longitudinal data. *Biometrics, 38*(4), 963-974.
- Li, F., Duncan, T. E., & Hops, H. (2001). Examining developmental trajectories in adolescent alcohol use using piecewise growth mixture modeling analysis. *Journal of Studies on Alcohol, 62*(2), 199-210.
- Marlatt, G. A., & Gordon, J. R. (1985). *Relapse prevention*. New York: Guilford Press.
- Marlatt, G. A., & Miller, W. R. (1984). *Comprehensive drinking profile*. Odessa, FL: Psychological Assessment Resources, Inc.
- Marques, A. C. P. R., & Formigoni, M. L. O. S. (2001). Comparison of individual and group cognitive-behavioral therapy for alcohol and/or drug-dependent patients. *Addiction*(6), 835-846.
- McCutcheon, A. L. (1987). *Latent Class Analysis*. Thousand Oaks, CA: Sage.
- McLachlan, G., & Peel, D. (2000). *Finite Mixture Models*. New York: John Wiley.
- Miller, W. R. (1989). Matching individuals with interventions. *Hester, Reid K., 157*(pp. 261-271).
- Miller, W. R., & Del Boca, F. K. (1994). Measurement of drinking behavior using the Form 90 family of instruments. *Journal of Studies on Alcohol*(Suppl. 12), 112-118.

- Miller, R. H., & Rollnick, S. (2002). *Motivational Interviewing: Preparing People for Change* (2nd ed.). New York: Guilford Press.
- Monga, N., Rehm, J. r., Fischer, B., Brissette, S., Bruneau, J., El-Guebaly, N., et al. (2007). Using latent class analysis (LCA) to analyze patterns of drug use in a population of illegal opioid users. *Drug and Alcohol Dependence*, 88(1), 1-8.
- Moos, R. H., & Moos, B. S. (2006). Rates and predictors of relapse after natural and treated remission from alcohol use disorders. *Addiction*, 101(2), 212-222.
- Moos, R. H., Moos, B. S., & Finney, J. W. (2001). Predictors of deterioration among patients with substance-use disorders. *Journal of Clinical Psychology*, 57(12), 1403-1419.
- Moos, R. H., Nichol, A. C., & Moos, B. S. (2002). Risk factors for symptom exacerbation among treated patients with substance use disorders. *Addiction*, 97(1), 75-85.
- Muthén, B. (2001a). Latent variable mixture modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *New Developments and Techniques in Structure Equation Modeling*: Lawrence Erlbaum Associates.
- Muthén, B. (2001b). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class-latent growth modeling. *Collins, Linda M.*
- Muthén, B. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrika*, 29(1), 81-117.
- Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative*

methodology for the social sciences (pp. 345-368). Newbury Park, CA: Sage Publications.

Muthén, B., & Muthén, L. K. (1998-2007). *Mplus User's Guide* (4th ed.). Los Angeles, CA: Muthén & Muthén.

Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, *24*(6), 882-891.

Nordstrom, G., & Berglund, M. (1987). A prospective study of successful long-term adjustment in alcohol dependence: social drinking versus abstinence. *J Stud Alcohol*, *48*(2), 95-103.

Nylund, K. L., Muthén, B. O., & Asparouhov, T. (in press). Deciding on the number of classes in latent class analysis: A Monte Carlo simulation study. *Structural Equation Modeling*.

Ojehagen, A., & Berglund, M. (1989). Changes of drinking goals in a two-year outpatient alcoholic treatment program. *Addictive Behavior*, *14*(1), 1-9.

Orford, J., Oppenheimer, E., & Edwards, G. (1976). Abstinence or control: The outcome for excessive drinkers two years after consultation. *Behaviour Research and Therapy*, *14*, 409-418.

Pachman, J. S., Foy, D. W., & Van Erd, M. (1978). Goal choice of alcoholics: A comparison of those who choose total abstinence vs those who choose responsible, controlled drinking. *Journal of Clinical Psychology*, *34*(3), 781-783.

- Perkins, H. W., Linkenbach, J., & Dejong, W. (2001). Estimated blood alcohol levels reached by "binge" and "nonbinge" drinkers: a survey of young adults in Montana. *Psychology of Addictive Behaviors, 15*(4), 317-320.
- Pettinati, H. M., Pierce, J. D., Jr., Belden, P. P., & Meyers, K. (1999). The relationship of Axis II personality disorders to other known predictors of addiction treatment outcome. *American Journal on Addictions, 8*(2), 136-147.
- Phibbs, C. S., Swindle, R. W., & Recine, B. (1997). Does case mix matter for substance abuse treatment? A comparison of observed and case mix-adjusted readmission rates for inpatient substance abuse treatment in the Department of Veterans Affairs. *Health Services Research, 31*(6), 755-771.
- Polich, J. M., Armor, D. J., & Braiker, H. B. (1981). *The course of alcoholism: Four years after treatment*. New York: Wiley.
- Project Match Research Group. (1993). Project MATCH: Rationale and methods for a multisite clinical trial matching patients to alcoholism treatment. *Alcoholism: Clinical and Experimental Research, 17*(6), 1130-1145.
- Project Match Research Group. (1997). Project MATCH secondary a priori hypotheses. *Addiction, 92*(12), 1671-1698.
- Project Match Research Group. (1998). Matching alcoholism treatments to client heterogeneity: Project MATCH three-year drinking outcomes. *Alcoholism: Clinical and Experimental Research, 22*(6), 1300-1311.
- Ramaswamy, V., DeSarbo, W., Reibstein, D., & Robinson, W. (1993). Empirical pooling approach to maketing mix elasticities with PIMS data. *Marketing Science, 12*, 103-124.

- Rindskopf, D. (2006). Heavy alcohol use in the "Fighting Back" survey sample: Separating individual and community level influences using multilevel latent class analysis. *Journal of Drug Issues. Special Issue: The "Fighting Back" program*, 36(2), 441-462.
- Rosenberg, H. (1993). Prediction of controlled drinking by alcoholics and problem drinkers. *Psychological Bulletin*, 113(1), 129-139.
- Sanchez-Craig, M., Annis, H. M., Bornet, A. R., & MacDonald, K. R. (1984). Random assignment to abstinence and controlled drinking: Evaluation of a cognitive-behavioral program for problem drinkers. *Journal of Consulting and Clinical Psychology*, 52, 390-403.
- Sanchez-Craig, M., Neumann, B., Souzaformigoni, M., & Rieck, L. (1991). Brief treatment for alcohol dependence: Level of dependence and treatment outcome. *Alcohol and Alcoholism*, 51, 515-518.
- Sanchez-Craig, M., Spivak, K., & Davila, R. (1991). Superior outcome of females over males after brief treatment for the reduction of heavy drinking: Replication and report of therapist effects. *British Journal of Addiction*, 86, 867-876.
- Satorra, A. (2000). Scaled and adjusted restricted tests in multi-sample analysis of moment structures. In R. D. H. Heijmans, D. S. G. Pollock & A. Satorra (Eds.), *Innovations in multivariate statistical analysis. A Festschrift for Heinz Neudecker* (pp. 233-247). London: Kluwer Academic Publishers.
- Schuckit, M. A. (1998). Binge drinking: The five/four measure. The editor responds. *Journal of Studies on Alcohol*, 59, 123-124.

- Schulenberg, J., O'Malley, P. M., Bachman, J. G., Wadsworth, K. N., & Johnston, L. D. (1996). Getting drunk and growing up: Trajectories of frequent binge drinking during the transition to young adulthood. *Journal of Studies on Alcohol, 57*(3), 289-304.
- Schwartz, G. (1978). Estimating the Dimension of a model. *The Annals of Statistics, 6*, 461-464.
- Shaw, G. K., Waller, S., McDougall, S., MacGarvie, J., & Dunn, G. (1990). Alcoholism: a follow-up study of participants in an alcohol treatment programme. *British Journal of Psychiatry, 157*, 190-196.
- Skinner, H. A. (1982). The Drug Abuse Screening Test. *Addictive Behaviors, 7*, 363-371.
- Skinner, H. A., & Allen, B. A. (1982). Alcohol dependence syndrome: Measurement and validation. *Journal of Abnormal Psychology, 91*, 199-209.
- Sobell, L. C., & Sobell, M. B. (1982). Alcoholism treatment outcome evaluation methodology. In National Institute on Alcohol Abuse and Alcoholism (Ed.), *Prevention, intervention and treatment: Concerns and models* (pp. 369-382). Rockville, MD: National Institute on Alcohol Abuse and Alcoholism.
- Sobell, L. C., & Sobell, M. B. (1992). Timeline Followback: A technique for assessing self-reported alcohol consumption. In R. Z. Litten & J. Allen (Eds.), *Measuring alcohol consumption: Psychosocial and biological methods* (pp. 41-72). Towota, NJ: Humana Press.
- Sobell, L. C., Sobell, M. B., & Agrawal, S. (in press). A randomized trial comparing a Guided Self-Change cognitive-behavioral motivational intervention in a group

versus individual setting for individuals with substance abuse disorders.

Psychology of Addictive Behaviors.

Sobell, M. B., & Sobell, L. C. (1993). *Problem drinkers: Guided self-change treatment.*

New York: Guilford Press.

Sobell, M. B., & Sobell, L. C. (1995). Controlled drinking after 25 years: How important was the great debate? *Addiction, 90*, 1149-1153.

Sobell, M. B., & Sobell, L. C. (1999). Stepped care for alcohol problems: An efficient

method for planning and delivering clinical services. In J. A. Tucker, D. A.

Donovan & G. A. Marlatt (Eds.), *Changing addictive behavior: Bridging clinical and public health strategies* (pp. 331-343). New York: Guilford Press.

Sobell, M. B., & Sobell, L. C. (2000). Stepped care as a heuristic approach to the treatment of alcohol problems. *Journal of Consulting and Clinical Psychology, 68*(4), 573-579.

Sobell, M. B., & Sobell, L. C. (2002). Introduction to the special section: Clinically useful assessment instruments for substance abuse. *Behaviour Research and Therapy, 40*(11), 1327.

Sobell, M. B., & Sobell, L. C. (2005). Guided Self-Change treatment for substance abusers. *Journal of Cognitive Psychotherapy 19*(199-210).

Sobell, M. B., Sobell, L. C., & Gavin, D. R. (1995). Portraying alcohol treatment outcomes: Different yardsticks of success. *Behavior Therapy, 26*(4), 643-669.

Sobell, M. B., Sobell, L. C., & Leo, G. I. (2000). Does enhanced social support improve outcomes for problem drinkers in guided self-change treatment? *Journal of Behavior Therapy and Experimental Psychiatry, 31*(1), 41-54.

- Vakili, S., Sobell, L. C., Sobell, M. B., Simco, E. R., & Agrawal, S. (2008). Using the Timeline Followback to determine time windows representative of annual alcohol consumption with problem drinkers. *Addictive Behaviors, 33*(9), 1123-1130.
- Wechsler, H., Lee, J. E., Kuo, M., & Lee, H. (2000). College binge drinking in the 1990s: A continuing problem: Results of the Harvard School of Public Health 1999 College Alcohol Study. *Journal of American College Health, 48*(5), 199-210.
- Weiss, R. D., Jaffee, W. B., deMenil, V. P., & Cogley, C. B. (2004). Group therapy for substance use disorders: What do we know? *Harvard Review of Psychiatry, 12*(6), 339-350.
- Wiesner, M., & Windle, M. (2004). Assessing covariates of adolescent delinquency trajectories: A latent growth mixture modeling approach. *Journal of Youth and Adolescence, 33*(5), 431-442.
- Wilkinson, D. A., & Carlen, P. L. (1980). Neuropsychological and neurological assessment of alcoholism: Discrimination between groups of alcoholics. *Journal of Studies on Alcohol, 41*, 129-139.
- Witkiewitz, K. (2008). Lapses following alcohol treatment: modeling the falls from the wagon. *Journal of Studies on Alcohol and Drugs, 69*(4), 594-604.
- Witkiewitz, K., & Masyn, K. E. (2008). Drinking trajectories following an initial lapse. *Psychology of Addictive Behaviors, 22*(2), 157-167.
- Witkiewitz, K., van der Maas, H. L. J., Hufford, M. R., & Marlatt, G. A. (2007). Nonnormality and divergence in posttreatment alcohol use: Reexamining the Project MATCH data "another way." *Journal of Abnormal Psychology, 116*(2), 378-394.

- Wu, J., & Witkiewitz, K. (2008). Network support for drinking: an application of multiple groups growth mixture modeling to examine client-treatment matching. *Journal of Studies on Alcohol and Drugs*, 69(1), 21-29.
- Yalom, I., & Leszcz, M. (2005). *The theory and practice of group psychotherapy* (5th ed.). New York: Basic Books.
- Zucker, R. A. (1994). Pathways to alcohol problems and alcoholism: A development account for the evidence for multiple alcoholisms and for contextual contributions to risk. In R. A. Zucker, G. Boyd & J. Howard (Eds.), *The Development of Alcohol Problems: Exploring the Biopsychosocial Matrix of Risk*. NIAAA Research Monograph No. 26 NIH Publications No. 94-3495 (pp. 255-289). Rockville, MD: Department of Health and Human Services.