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Uncovering Multiple Pathways to Substance Use: A comparison of methods for identifying population subgroups

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Abstract

This paper describes and compares a selection of available modeling techniques for identifying homogeneous population subgroups in the interest of informing targeted substance use intervention. We present a nontechnical review of the common and unique features of three methods a) trajectory analysis b) functional hierarchical linear modeling (FHLM) and c) decision tree methods. Differences among the techniques are described including required data features, strengths and limitations in terms of the flexibility with which outcomes and predictors can be modeled, and the potential of each technique for helping to inform the selection of targets and timing of substance intervention programs.

Keywords

quantitative methods; person-centered; trajectories; decision tree methods; Functional Hierarchical Linear Modeling

Introduction

Targeted intervention programs intended in full or in part to reduce rates of substance use, abuse and dependence have aimed their efforts at “high-risk” groups defined by early signs or symptoms that have been demonstrated in longitudinal research as potent predictors of substance use behavior. Examples of targeted substance use intervention include programs aimed at children of substance abusing parents (Kumpfer, Alvarado, Tait, & Whiteside, 2007), deviant youth (Bierman et al., 2007) and adolescents from impoverished socioeconomic backgrounds (Botvin, Griffin, Diaz, & Ifill-Williams, 2001). The fact that these programs often differ not only in terms of samples targeted, but also in basic program content and theoretical underpinnings, demonstrates the implicit expectation that different rather than common developmental pathways may explain the emergence of substance use among diverse population subgroups.

Despite widespread acceptance of the concept of multiple pathways from a theoretical (Cicchetti & Rogosch, 1996) as well as a practice perspective (Babor & Caetano, 2006; Babor & Del Boca, 2003), the delineation of these pathways through empirical work has been partially impeded by an over-reliance on *variable-centered* analyses which evaluate potential predictors of substance use representing population averages rather than individual

variability (Bates, 2000; Bauer & Shanahan, 2007). The results of variable-centered approaches, in fact, have been demonstrated as least generalizable to those individuals exhibiting the largest deviations from the average (Labouvie, Pandina, & Johnson, 1991) and may inadequately characterize associations between potential risk/protective factors and substance use outcomes for the majority of individuals in a given sample (Block & Robins, 1993; Magnusson & Stattin, 2006).

The goal of understanding heterogeneity in the developmental pathways to and through substance use have given rise to the advancement and use of several pattern-centered statistical techniques (sometimes referred to as person-centered or group-based) that allow for the study of individual differences in behaviors and the relationships among established risk and/or protective factors within and between population subgroups (Bergman, von Eye, & Magnusson, 2006). With the goal of disaggregating representative samples into coherent subsets of persons who are similar to each other based on specific patterns of behavior, these techniques organize data by identifying sets of like individuals on the basis of their exposure to a combination of risk/protective factors and/or the developmental trajectory of behavior that they follow. Together, these approaches may provide a promising strategy for uncovering multiple developmental pathways and informing the targets, content and timing of substance intervention.

The aim of this paper is to describe and compare a selection of available pattern-centered modeling techniques. Specifically, we present a nontechnical review of the common and unique features of three methods a) trajectory models b) functional hierarchical linear modeling (FHLM) and c) decision tree methods. While many excellent technical references describing these methods are already available (Brieman, Friedman, Olshen, & Stone, 1984; Jung & Wickrama, 2008; Lemon, Roy, Clark, Friedmann, & Rakowski, 2003; Li, Tammy L; Shiffman, Saul, 2006; Muthén & Muthén, 2000; Nagin, 2005), our review focuses on how research questions might be addressed with these methods as well as discusses data features that are most appropriate for their use (see Table). The selected methods represent a small number of alternative techniques with similarities and differences in terms of their ability to accommodate different study designs, their requirements for measurement of predictors and outcome and the level to which each method has previously been disseminated in both the technical and substantive literature. We note that several other pattern-centered techniques are newly being used in substance use research. These include latent class analysis (e.g. Buettner, Bartle-Haring, Andrews & Khurana, 2010) and its longitudinal extension, latent transition analysis (e.g. Maldonado-Molina, Collins, Lanza, Prado, Ramirez & Canino, 2007), as well as time series analysis (e.g. Dierker, Lloyd-Richardson, Stolar, Flay, Tiffany, Collins, Bailey, Nichter, Clayton & TERN, 2006) and factor mixture analysis (e.g. Hildebrandt, Langenbucher, Carr & Sanjuan, 2007). While a consideration of each of these techniques is beyond the scope of a single paper, we hope to provide a model comparison that will allow readers to focus on the most critical considerations in evaluating pattern-centered methods.

Trajectory Analysis

Pattern-centered trajectory analysis, also known as growth mixture modeling and semiparametric group-based modeling (Gritz et al.; Muthén & Muthén, 2000; Nagin, 2005) is a group of techniques based on a finite mixture model that has been used to map population heterogeneity in the development of substance use behavior. With the goal of identifying subgroups that follow distinct trajectories of substance use over time (in contrast to general growth modeling which evaluates the average population trajectory), this analytic technique 1) tests for the presence of diverse developmental trajectories; 2) identifies the appropriate number of trajectories; and 3) evaluates the fit of each individual in terms of

their likelihood of following each trajectory (see Figure 1 for hypothetical smoking trajectories based on trajectory analyses).

To date, trajectories of smoking behavior have been the most extensively studied substance, using these techniques. Based on different samples, longitudinal periods of assessment, and measurement of smoking behavior, evidence for three (White, Pandina, & Chen, 2002), four (Audrain-McGovern et al., 2004), five (Abroms, Simons-Morton, Haynie, & Chen, 2005; Colder, 2001; Guo et al., 2002), and six (Chassin, Presson, Pitts, & Sherman, 2000; Costello, Dierker, Jones, & Rose, 2008; Lessov-Schlaggar et al., 2008; Orlando, Tucker, Ellickson, & Klein, 2004; Stanton, Flay, Colder, & Mehta, 2004) distinct smoking trajectory groups have been described, providing evidence for multiple developmental patterns of smoking. The major strength of these trajectory methods is their ability to provide a more developmentally informed way in which the behavioral outcome can be characterized, that is, by considering behavioral change over time as the outcome of interest, rather than the traditional measurement of outcome at a single point in time. While most empirical work has focused on the timing, rate and intensity of substance use across time, more recently, symptoms of abuse and dependence have also been modeled with these techniques (e.g. Chung, S. Maisto, Cornelius, Martin, & Jackson, 2005; Hu, Muthén, Schaffran, Griesler, & Kandel, 2008; Jackson, Sher, & Wood, 2000).

Collectively, this work has important implications for the identification of individuals who will experience the most substantial and impairing substance use outcomes. That is, investigations of trajectories from early adolescence to and through adulthood provide a unique opportunity to disentangle subgroups that will engage in relatively benign substance experimentation or those who will experience early remission of substance use behavior from those who will engage in problematic and/or chronic use. In this way, the empirical convergence of substance use trajectories across studies may reveal the groups of substance users most in need of intervention. This is achieved not only through the identification of trajectory subgroups, but also by examining associations between individuals following different patterns of development and future consequences associated with those heterogeneous trajectories (Hill, White, Chung, Hawkins, & Catalano, 2000; Muthén & Muthén, 2000; Schulenberg, O'Malley, Bachman, Wadsworth, & Johnston, 1996; White, Bates, & Labouvie, 1998). For example, Muthén and Shedden found that a subgroup of individuals with increasing binge drinking behavior between age 18 and 24 had the highest probability of developing alcohol dependence compared to individuals exhibiting high rates of binge drinking at baseline and those reporting a relatively low, normative frequency of binge drinking behavior (Muthén & Shedden, 1999).

Trajectory models also have the advantage of a great deal of flexibility in the specification of time. For example, change in substance use outcomes can be modeled for a series of distinct developmental stages (e.g., adolescence vs. young adulthood vs. middle adulthood). These piecewise trajectory models permit estimation of separate rates of change during critical developmental time periods or before and after the delivery of an intervention, and can be useful for identifying important transition points. For example, Li and colleagues tested a piecewise GMM in which they estimated change over time in adolescent alcohol use separately for two critical developmental periods (middle school – 6th to 8th grade, and high school – 9th to 12th grade). Most studies have used piecewise trajectory models to evaluate change in substance use behaviors over distinct developmental age periods (c.f. Li, Duncan, Duncan, & Hops, 2001; Fuzhong Li, Duncan, & Hops, 2001), but piecewise models are also recommended for intervention evaluation studies where change in substance use outcomes over time can be modeled separately for pre- and post-intervention time periods to isolate change during the intervention period and to determine the rate at which intervention effects change following termination of the intervention (c.f. Brown et al., 2008).

In addition to the developmentally informed way in which these analyses can describe homogenous subgroups whose substance use is differentially characterized by quantity, chronicity of use, and/or the timing of onset and progression, trajectory analyses also have the potential to more directly inform the presence of multiple developmental pathways through the inclusion of established risk or protective factors/predictors in the trajectory model. This important step can both validate the distinctiveness of the identified trajectory groups and also provide information about differences in the constellations of risk/protective factors that may be linked to the likelihood of an individual following one trajectory over another. While the most consistent findings have demonstrated that established risk factors are associated with higher odds of membership in each of the substance use trajectory groups compared to nonusers (Audrain-McGovern et al., 2004; Costello, Dierker, Jones, & Rose, 2008; Hill, White, Chung, Hawkins, & Catalano, 2000; Orlando, Tucker, Ellickson, & Klein, 2004) in several cases, differences between substance user subgroups have also been established. As an example, Chassin and colleagues (Chassin, Presson, Pitts, & Sherman, 2000) empirically identified six trajectories, two of which included substantial smoking in middle adulthood (i.e. the early stable and late stable trajectory groups). Important differences in adolescent and young adult psychosocial variables were found between these two groups, despite both groups having reached similar young adult smoking levels and experiencing an inability to quit. Thus, the causal mechanisms very likely differ based on the presence of dissimilar risk. For example, late escalators have been consistently shown to display low risk profiles in terms of drug use (Costello, Dierker, Jones, & Rose, 2008; Orlando, Tucker, Ellickson, & Klein, 2004; Stanton, Flay, Colder, & Mehta, 2004), and both peer smoking and deviance (Chassin, Presson, Pitts, & Sherman, 2000; Costello, Dierker, Jones, & Rose, 2008; Orlando, Tucker, Ellickson, & Klein, 2004), suggesting that these factors may be inappropriate targets for this subgroup of the population at risk for chronic smoking.

Importantly, while, the outcome in these studies is developmentally informed by the measurement of substance use behavior at several points in time, with the exception of those studies using *dual* or *joint* trajectory analyses (see Chung, Maisto, Cornelius, Martin, & Jackson, 2005; Jester et al., 2008) in which trajectories of two different behaviors are empirically linked, few have considered risk/protective factors in a developmentally informed way. That is, despite the ability of trajectory models to consider the time varying nature of risk in the form of dual or joint trajectories (Nagin, 2005), the vast majority of studies have examined risk factors measured at the first wave of assessment. Further, like traditional regression analyses, the focus is most often on main effects that quantify the association between an individual risk factor and the likelihood of following one trajectory over another. Given that our search for multiple pathways involves questions about how risk/protective factors may work synergistically, trajectory analyses have to date, not always been well used in terms of a consideration of more complex risk/protective pathways.

Although planned interactions are also tested when the sample is adequately large, these have most commonly included interactions between a single risk/protective factor and demographic indicators such as gender, ethnicity or age. While these interactions allow for an exploration of nonlinear relationships between specific pairs of variables and the likelihood of trajectory membership, they may also represent an overemphasis on parsimony that may not characterize the most meaningful interactions or risk/protective factor constellations associated with problem substance use behavior. Thus, while trajectory analyses have been extremely informative in identifying the heterogeneity in the timing, rate and intensity of substance use progression, the limitations of real world data have in some cases precluded a careful exploration of hypotheses regarding ways in which *multiple* risk and/or protective factors may *work together* to promote or reduce specific substance use outcomes. For a more detailed description of trajectory analyses, there are several technical

papers (Gritz et al.; Muthén & Muthén, 2000; Nagin, 2005) and empirical examples (Audrain-McGovern et al., 2004; Costello, Dierker, Jones, & Rose, 2008; Hill, White, Chung, Hawkins, & Catalano, 2000; Orlando, Tucker, Ellickson, & Klein, 2004; Chassin, Presson, Pitts, & Sherman, 2000) available.

Functional Hierarchical Linear Modeling

While determinants of substance use behavior include distal factors such as those measured in traditional longitudinal studies with one or more years between assessment points (e.g. previous substance use or family history of substance use), they also include factors and circumstances proximal to the time that substance use actually takes place (e.g. characteristics of the physical and social environment, actions of peers, the individual's feelings or state of mind, subjective feelings of withdrawal, and so on). As such, the collection of intensive longitudinal data (i.e. 50 or more waves of assessment) has begun to have a significant impact on the substance use field as well as on the planning of intervention. Measuring these rapidly changing phenomena along with substance use behavior and establishing relationships among them requires a fine-grained approach, involving measurement occasions at frequent intervals over time (Collins & Graham, 2002). Thus, in many cases, the careful study of the determinants of substance use onset, maintenance, cessation, and relapse now includes 50 or more waves of assessment with measurement intervals on the order of weekly, daily, or even several times a day (Dierker et al., 2006; Freedman, Lester, McNamara, Milby, & Schumacher, 2006; Hopper et al., 2006; Shiffman et al., 2007).

Functional Hierarchical Linear Modeling (Li, Root & Shiffman, 2006) is a newly emerging method that has the potential to uncover the presence of population subgroups. Unlike trajectory analysis, however, FHLM is more directly suited to the modeling of intensive longitudinal data in which observations are numerous across time (Walls & Schafer, 2006). Similar to trajectory analyses, the shapes of unique trajectory groups within the population are first evaluated. However, rather than limiting the description of change in substance use behavior to relatively simple shapes as is done in trajectory models (i.e. linear, quadratic or cubic), FHLM allows for change to be directly modeled and described (Li, Root & Shiffman, 2006). That is, in practice, substance use may go up and down repeatedly over a day, week, month or year rather than following these more idealized patterns. By employing non-parametric regression techniques, FHLM directly estimates the shapes of trajectories according to information derived from the data instead of assuming certain restricted or even unreasonable shapes. In FHLM, the only underlying assumption regarding the trajectory shapes is that the change of outcome over time is smooth (see Figure 2 for hypothetical smoking trajectories based on FHLM).

Aside from FHLM's ability to directly model fine-grained change in substance use over time, this method can also evaluate the presence of the time varying effects of potential covariates (i.e. risk/protective factors) on these patterns of change. While pattern-centered trajectory models have previously been able to evaluate the average association between time varying covariates and individual trajectories, FHLM has the added ability to test how these effects may change over time for trajectory groups. In other words, rather than testing only an average effect that a covariate may have on changing substance use behavior, FHLM also has the capacity to test whether a covariate (e.g. family history of alcohol abuse or parental monitoring) has either a consistent or time varying effect on the alcohol use trajectories of unique population subgroups. FHLM may uncover, for example, that for those following an early escalating trajectory, a family history of alcohol has a stronger effect during early and late adolescence than during early adulthood (or vice versa). In this way, FHLM provides the opportunity to evaluate previously unanswerable questions such as how the relationship between risk/protective factors and substance use may change over time as

well as the direction and strength of these associations. While both trajectory analyses and FGLM are able to evaluate time varying covariates (i.e. variables that are measured at each wave of assessment whose values change over time) (e.g. Nagin, 2005), only FGLM can model these time-varying effects (i.e. change in the relationship between a risk/protective factor and a substance use outcome over time) (Li, Root & Shiffman, 2006). To date, FGLM does not yet include a piecewise feature permitting estimation of separate rates of change during different developmental time periods or before and after the delivery of an intervention. For a more detailed description of FGLM, the reader is encouraged to consult Li, Root & Shiffman, 2006).

Decision Tree Methods

When the goal of one's research is not to establish behavior trajectories, but rather, to define population subgroups based on the complex interplay among established risk/protective factors, a flexible analytic alternative are decision tree methods, such as Classification and Regression Tree analysis (CART) (Breiman, Friedman, Olshen, & Stone, 1984). Unlike trajectory analyses and functional hierarchical linear modeling which center on identifying diversity in behavioral outcomes, decision tree techniques can classify individuals according to unique "initial conditions" that may include a constellation of risk/protective factors both unique to a subgroup within the population; and distinct from the risk/protective constellation of other subgroups that exhibit the same outcome.

Specifically, decision tree models proceed by making binary splits in a sample in order to separate individuals based on each decision into the "purest" high-risk and low-risk subgroups with respect to a specific outcome of interest. A unique strength of decision tree methods is the ability to reveal nonlinear associations between risk/protective factors and the outcome of interest and ultimately to generate hypothesized pathways (operationalized as branches) that best describe subgroups with high (and low) proportions of individuals exhibiting a particular substance use outcome. All possible separations (categorical) or cut points (continuous) are tested by comparing the chi-square statistic in relation to the outcome. If a variable such as age (i.e. a continuous variable) is considered, every possible age split is considered and then evaluated according to which separates the participants into the purest high-risk and low-risk subgroups. Through this process, a decision tree is generated in which each of the variables in the model is assessed at each decision point including the variables on which the previous splits were made. In this way, the method is particularly suited to an elucidation of unique risk/protective constellations and the resulting models can generate multiple unique subgroups. That is, subgroups showing similar substance use outcomes, but different premorbid risk/protective factor constellations can be elucidated.

As an example, the alcohol abuse tree in the following figure, based on hypothetical data, models lifetime alcohol abuse as the outcome and includes such risk/predictor variables as lifetime marijuana use (yes/no), age, gender, and deviance. The final tree model contains 9 nodes with 4 internal ones (pentagons) and 5 terminal ones (squares). Each internal node represents a decision point. For each node, the number of participants of the outcome variable and the predictor variable and cut point used to form the nodes are listed. The binary marijuana use variable was the first variable to empirically separate the group into high and low risk subgroups. The modeling procedure made further subdivisions with the following variables: a deviant behavior score, age, and gender. Terminal nodes (squares) represent final groupings. Larger numbers of individuals with alcohol abuse fall in nodes in the right side of the model. Overall, the model correctly identified 89% of participants who abuse alcohol and 72% of those who do not.

As the tree diagram illustrates, deviant adolescents who have not used marijuana previously, have a better prognosis in terms of alcohol abuse particularly if younger than 16 and female. Of the participants who had used marijuana, no additional covariates helped to classify alcohol abuse. Therefore, this model may suggest two pathways to alcohol abuse: One is through marijuana experimentation and the other is through additional deviant behavior. The deviant behavior pathway is important mainly for males who are 16 years old and older.

Given that decision tree methods typically require the selection of a single outcome of interest (e.g. alcohol abuse) rather than modeling an empirically defined outcome trajectory, it must handle trajectory-like features of substance use behavior (e.g. chronicity, onset, and progression) through their inclusion in the model as one or more of several predictors. For example, in a recent study employing CART to examine heterogeneity in outcome following treatment for smoking cessation, Swan and colleagues included in their list of predictors of smoking behavior 3 and 12 month post treatment, such premorbid smoking features as years smoked prior to treatment and the presence of previous quit attempts (Swan, Javitz, Jack, Curry, & McAfee, 2004). Alternately, in a study evaluating the presence of multiple population subgroups at risk for increasing smoking behavior within adolescence, three separate CART models were tested based on a priori groupings of change seen in smoking (Dierker, Avenevoli, Goldberg, & Glantz, 2004). The presence of unique risk/protective factor constellations were evaluated separately for individuals moving from a) a nonsmoker status to experimental smoking during the 1 year follow-up assessment; b) a nonsmoker status to regular smoking; and c) from experimental smoking to regular smoking.

Although decision tree methods are considered exploratory in nature, specific hypotheses related to the presence of unique subgroups can be tested. Rather than allowing the model to select a primary variable with which to split the sample into high and low risk groups, the researcher may choose to select a variable as the primary split. For example, if you are interested in health disparities and have demonstrated, possibly through more traditional linear regression techniques, differences in terms of the associations between risk factors and substance use outcomes for Black vs. White participants, you may choose to include a race variable as the first model split. High and low risk subgroups for the substance outcome of interest would then be empirically determined for each racial group. This somewhat more planned model building approach can be evaluated through an “importance score” which measures the choice of a particular predictor against the other candidate predictors. For example, it is possible that risk/protective factors other than those that represent primary splits in the model can be of importance in the prediction of the substance use outcome. When predictors are for example highly correlated (e.g. mother’s education and father’s education) (Steinberg & Golovnya, 2007), only one is likely to be selected for the model. The absence of the alternate variable from the model does not then suggest that it is unimportant, but rather that it is “masked” by the other. For each step of a decision tree model, an importance measure can be calculated for each variable that was not selected as the predictor. The importance measure reflects the improvement that would be attributable to each variable in its role as a surrogate to the selected predictor. The values of these improvements are summed, and are scaled relative to the best performing variable (Steinberg & Golovnya, 2007). In short, the importance score can be used as a measure of a variable’s ability to mimic the chosen tree and to play the role as stand-in for variables appearing as primary splits in the decision tree.

Unlike trajectory analysis and FGLM, decision tree methods specifically allow for a data driven exploration of nonlinear relationships between predictors and outcome, and have the potential to fit numerous interactions that cannot be handled as efficiently with either traditional regression techniques or other pattern centered methods. While not requiring longitudinal data, decision tree methods can be used to empirically link risk/protective factor

constellations at earlier waves of assessment with substance use outcomes measured at a later time point (Dierker, Avenevoli, Goldberg, & Glantz, 2004; Swan, Javitz, Jack, Curry, & McAfee, 2004). Given that traditionally research on the development of substance use behavior has been able to achieve its goals with only a few waves of measurement, decision tree methods are often appropriate for evaluating population heterogeneity and the possible presence of multiple etiologies. Despite its potential however, within the substance use literature, it has to date been infrequently used (Dierker, Avenevoli, Goldberg, & Glantz, 2004; McKenzie et al., 2006; Swan, Javitz, Jack, Curry, & McAfee, 2004; Vik, Cellucci, Hedt, & Jorgensen, 2006) when compared to trajectory analysis. For a more detailed description of decision tree methods, there are technical papers (Brieman, Friedman, Olshen, & Stone, 1984; Steinberg & Golovnya, 2007; Zhang, H. & Singer, B., 1999) and empirical examples (Dierker, Avenevoli, Goldberg, & Glantz, 2004; Swan, Javitz, Jack, Curry, & McAfee, 2004) available.

Practical Considerations for use of these pattern-centered methods

Aside from differences among the three methods reviewed in terms of their ability to uncover the presence of multiple pathways to substance use and in doing so potentially inform the planning of intervention, many measurement and design details associated with a particular study should be considered when selecting among these pattern-centered alternatives. These more practical details are reviewed in the sections that follow.

Measurement

1. Outcome—In order to employ pattern-centered trajectory analyses and FHLM, at minimum, data must include identical measurement of the substance use outcome at each assessment wave. Thus, longitudinal designs in which measurement of the substance outcome changes developmentally (e.g. measurement of substance initiation in childhood and early adolescence vs. measurement of abuse and/or dependence in late adolescence or young adulthood) would not be easily accommodated by either of these methods. While the majority of empirical work to date has examined trajectories based on continuous measures of substance use, that is, number of cigarettes smoked, number of drinking occasions, or frequency of marijuana use, pattern-centered trajectories based on both trajectory analysis and FHLM techniques can also be defined based on binary (e.g. presence or absence of drug use), count (e.g. number of drug use incidents), or ordered data (e.g. no use, monthly use, weekly use, and daily use). Further, given the often high rate of zeros in substance use data (i.e. reports of no substance use across many individuals and/or observations), both of these methods are capable of addressing this issue by using a two-part model in which one part deals with zero-value observations and the other part deals with non-zero observations (Witkiewitz & Masyn, 2008).

By comparison, decision tree analysis focuses on substance use have been exclusively performed on binary outcome data (Dierker, Avenevoli, Goldberg, & Glantz, 2004; McKenzie et al., 2006; Swan, Javitz, Jack, Curry, & McAfee, 2004; Vik, Cellucci, Hedt, & Jorgensen, 2006), although the general approach to prediction can be applied to regression problems as well, in which the outcome of interest is continuous/count data. That is, rather than decision points in the model corresponding to correct and incorrect classification rates on a binary outcome, decision points will instead correspond to generally higher or lower values on the continuous outcome. The average value of the continuous substance outcome would be estimated among those participants at each decision point (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). For situations in which count, or ordered outcomes are available, observations would generally need to be dichotomized for use in decision tree models.

2. Predictors—Each of the three methods reviewed in this paper are appropriate for use with predictors that are binary, ordered, and count data. In a decision tree model, predictors are selected based on their ability to accurately classify cases in terms of the selected outcome. Alternately, the inclusion of predictors in a trajectory or FHLM model evaluates the change in the likelihood of membership in each trajectory group compared to a reference group based on different levels of the predictor (Muthén & Muthén, 2000; Nagin, 2005). That is, they can influence which trajectory group a person is most likely to belong to. While early work using this method most commonly included a single reference group (e.g. Abroms, Simons-Morton, Haynie, & Chen, 2005), more recent work has examined each class in turn as a reference group in order to evaluate the likelihood of membership in each trajectory group with regard to predictors (e.g. Audrain-McGovern et al., 2004; Costello, Dierker, Jones, & Rose, 2008).

Trajectory models have also been extended to include simultaneous modeling of a time varying predictor and outcome (c.f. Chung, Maisto, Cornelius, Martin, & Jackson, 2005; Jester et al., 2008; Witkiewitz & Masyn, 2008). These more general joint trajectory (or parallel process) growth mixture models permit examination of the relations between two behavioral trajectories as they change over time. Specifically, the joint probability of membership in trajectory classes for both outcomes can be examined. For example, Chung and colleagues examined relations between changes in alcohol use and DSM-IV alcohol symptom severity over the course of one year in adolescents with a lifetime DSM-IV alcohol use disorder diagnosis (Chung, Maisto, Cornelius, Martin, & Jackson, 2005). They found that use and symptom severity were moderately associated over time, with the highest probability of joint group membership occurring for an abstainer alcohol use class and a very low symptom severity class. However, they also found variability in joint probability in other classes of use and symptom severity, suggesting a potential discrepancy in expected parallel development of increasing alcohol use and increasing symptom severity. Although dual trajectory analysis (two parallel processes included) has been more popular in practice, triple (or more) trajectories can be modeled with currently available software, e.g. PROC TRAJ. To date, however, the data requirements and interpretability of these more complex models has not been evaluated.

3. Covariates—In trajectory analysis, covariates are different from predictors in that covariates are used to specify the trajectories (i.e. their inclusion may change the number or shape of trajectories defined by the model), but not to predict the membership probability of belonging to a certain trajectory. Unlike predictors, covariates represent events or characteristics that can lead to changes in the trajectory itself. By including covariates (time stable or time varying), subgroups are defined not only by the shape of trajectories but also by the relationship between outcome and covariates during the course of a trajectory. This should in general lead to a more sensible description of the behaviors of each subgroup and hence help in revealing more useful details in substance use behavior. Notably, although linear relationships between outcome and covariates is always assumed in current trajectory analysis, FHLM is capable of relaxing this restriction and exploring more complicated (e.g. time-varying relationships between outcome and covariates).

4. Assumptions—As is the case when any statistical analysis is undertaken, it is important to consider the statistical method's critical assumptions. Some of these assumptions are made by the researchers (e.g., existence of homogenous subgroups in the population), while other can be assessed through direct examination of the data (e.g., frequency distribution of the outcome, covariance structure of the repeated measures, general shape of change in the outcome) prior to analysis. Inaccurate assumptions can result in biased parameter estimates, inaccurate standard errors and test statistics, and misleading

conclusions (e.g., concluding that there are more classes or subgroups than actually exist in the population).

The key assumption in trajectory analysis is the heterogeneity assumption which says that heterogeneity in the population under study results from the existence of several homogeneous subgroups (classes) in term of the behavior. However, the participants' indexes of class membership are not observable, and are considered latent (Muthen & Muthen, 2000, Nagin, 2005). The second assumption in trajectory analysis focuses on the frequency distribution of the outcomes conditional on a latent class. That is, for different types of outcomes (binary, count and continuous), different distributions might be employed. The covariance structure among the repeatedly measured outcomes is also an important assumption within trajectory analysis. This is in general similar to those assumptions used in classical longitudinal analysis, where it is important to correctly specify the nature of the correlation among the repeated measures. The third assumption deals with the shape of trajectory, i.e. the shape of change of outcome over time. In general, the trajectories are assumed to have a polynomial (linear, quadratic or cubic) form with the only exception, to our knowledge, being Shedden and Zucker (2008). This shape is specified by the researcher in the formulation of the model to be tested. When predictors are included, a logistic regression model is in general assumed to link group membership probability to predictors, and when covariates are included, a linear relationship with time-stable coefficients between outcome and covariates is generally assumed, although the coefficients of the covariates might be assumed to be random to take into account individual level variability. That is, although the values of the covariates may vary over time, their relation to the outcome is assumed to be the same at every time point (i.e., the effect of the covariate on the trajectory is constant over time).

FHLM inherits most of the above assumptions but relaxes the restrictions on the shape of trajectories and on the relationship between outcome and covariates. Instead of assigning a specific form to the trajectory, FHLM only assumes the trajectory to be smooth and then estimates the shape of the trajectory based on observed data. In addition, the relationship between outcome and covariates is allowed to change over time instead of being constant over the course of trajectory.

In contrast, decision tree methods represent non-parametric techniques for which assumptions about the distribution of predictors or outcome are not made. Thus, decision trees can handle numerical data that are highly skewed (i.e. an asymmetrical distribution of values) or multimodal (i.e. the relatively frequent occurrence of multiple values), as well as categorical predictors that are ordered or discrete (i.e. including a limited number of integer values). Given that the results of decision tree models for classification (binary outcomes) or regression (continuous outcomes) can be summarized based on logical if-then conditions, it does not require the assumption that the underlying relationships between the predictor variables and the outcome variable are linear.

5. Missing data—In both trajectory modeling and FHLM, missing data on the trajectory measures (i.e. substance use outcomes across time) and on time-varying variables are handled with a maximum likelihood approach (Nagin, 2005) together with the missing-at-random assumption, which assumes that, for each individual, the likely values for missing data on the trajectory and time-varying variables can be estimated from other available observed data. That is, this approach uses available information on each case for constructing the trajectories rather than deleting individuals with missing observations. Similar to conventional regression methods, however, pattern-centered trajectory models cannot accommodate cases with missing data on time stable predictor variables (e.g. gender, ethnicity, etc.). Thus, when time stable predictors of trajectories are introduced into the

model, cases with missing data on one or more of these predictors are dropped from the analysis. This creates the potential for the basic trajectory model (i.e. the model before predictors are introduced) to be based on a larger and potentially different sample. One option for correcting this would be to drop from the basic model those cases with missing data on the predictor variables. However, the loss of information and potential introduction of bias should be carefully considered before this strategy is selected (Collins & Lanza, in press). An alternate strategy for handling missing data on time stable variables in trajectory analyses would be to use multiple imputation (Schafer & Graham, 2002), a simulation-based approach where several complete data sets are created by imputing values for the missing data. Notably, however, while this approach preserves information and statistical power, it also supposes a single population within the data, an assumption that is at odds with the multiple subgroups hypotheses being tested with pattern-centered modeling approaches (Colder, 2001).

In contrast, decision tree methods are unable to directly handle missing data on the outcome variable, but can classify participants with missing data on the predictor variables through the use of information from correlated predictors (i.e. surrogates). That is, if a participant cannot be classified into a high or low risk group due to a missing value, a surrogate predictor with the highest importance score (i.e. the calculation of the variable's ability to mimic the chosen model in terms of accurate classification of those with and without the outcome of interest) is used for that participant (Steinberg & Golovnya, 2007). While a multiple imputation approach is again a possible strategy for handling missing values for both outcome and predictor variables, the hypothesized presence of multiple subgroups within the data may be at odds with the single population assumption that multiple imputation involves. In a recent study in which surrogate splits and statistical imputation were directly compared in a CART model, imputation tended to outperform surrogate splits in terms of predictive accuracy (Feelders, 1999). Further, multiple imputation has the advantage of handling missing data in the predictors as well as the outcome variable, unlike the surrogate missing data procedures used by the CART algorithm.

Study Design

1. Number of Assessment Waves—The study design feature that most clearly distinguishes the three methods presented in this paper is the number of assessment waves that can be successfully modeled. Although there is one published example of using a decision tree technique for longitudinal data (Segal, 1992), generally, these methods are most appropriate for cross sectional data as well as data that include baseline assessment and a single longitudinal follow-up. In contrast, while varying numbers of assessment waves can be modeled with trajectory analyses, both lower and upper limits in terms of the longitudinal nature of the data are indicated. For example, for those studies that follow an *individual age cohort* across time and require evaluation of linear and quadratic developmental trajectories, at least 4 waves of assessment are required. This lower limit is not however required for studies that include *multiple age cohorts*. For example, numerous empirical papers have applied trajectory analyses to the first 3 waves of the AddHealth study, a nationally representative school based study collecting data from adolescents in multiple age cohorts (grade 7 through 12 at the first wave of assessment). Due to the multiple overlapping age cohorts assessed in AddHealth, the study provides an opportunity to examine developmental trajectories spanning early adolescence into young adulthood by “linking” the cohorts together based on age in a cohort-sequential design (Miyazaki & Raudenbush, 2000). In this way, each participant contributes information to only a part of the trajectory (e.g. a 7th grader at the start of the study would contribute to the building of trajectories from approximately age 13 to 18 while an 11th grader would contribute trajectory information from age 17 to 22).

Upper limits for the number of assessment waves that can be successfully modeled as multiple trajectories are also indicated. While trajectory analyses can computationally handle a large number of longitudinal observations, these analyses are limited by the shapes that can be evaluated (i.e. linear, quadratic or cubic). In contrast, FHLM does not require that the shapes of the trajectories be specified in advance, but rather, models more complicated shapes directly from the data.

2. Spacing of measurement occasions—For each of the three methods, the longitudinal spacing of measurement occasions in a data set can include either evenly spaced periods between measurement occasions (e.g. 1 week, month or year) or irregularly spaced periods (e.g. 1, 2 and 4 weeks/months/years). For the purpose of informing intervention, it is most appropriate when measurement is over a meaningful period in which change is expected and intervention might feasibly be targeted. This could include measurement 1) before, during and/or after a transition; or 2) across a previously demonstrated age of risk for the development of risk/protective factors, substance use behaviors and/or consequences of substance use (Collins & Graham, 2002).

3. Handling data based on a complex sampling design—Sample design refers to the procedures used to select a random sample. A complex sample design may include unequal probabilities (used to over- or under-represent a specific sub-population in the sample), stratification (used to select independent samples from different sub-populations), or multi-stage sampling (used to select on two or more levels of units imbedded one in the other, such as geographic areas (primary units), schools (secondary units), students (tertiary units)).

When complex sampling is used, sample weights (accounting for unequal probabilities in selection) as well as other design effects (stratification and multistage sampling) need to be included in the statistical model to obtain parameter estimates that accurately reflect the population of interest (Brogan, 2004). Whether or not complex sampling features can be modeled with these statistical techniques has to date been tied more closely to the software used to run the analyses than to the specific statistical method used. For example, when using MPlus to model longitudinal trajectories, sampling weighting as well as other design effects can be used in the estimation procedures (Muthén & Muthén, 1998–2007). In contrast, while PROC TRAJ can model case weights, it does not currently handle additional design effects. For data based on complex sampling, this would result in accurate tests of significance, but somewhat inaccurate standard errors. Similarly, the two of the most commonly used software packages for estimating decision tree models (CART Salford Systems and SPSS) each allow integration of the sampling weights, but do not allow for the modeling of design effects (e.g. selection strata and clustering). Currently, FHLM does not allow the use of either sample weights or design effects.

Notably, however, when using pattern-centered methods, consideration of sample weights and design effects may in many instances fail to serve the research question of greatest interest. That is, the goal may not be to derive nationally representative estimates, but rather to uncover homogeneous subgroups within a relatively diverse sample. Since nationally representative samples may mask characteristics of poorly represented groups, the choice to use the unweighted sample can improve one's ability to identify subgroups. For example, it is common in nationally representative samples to oversample various racial/ethnic groups and/or cohorts. This oversampling allows for increased power to detect potentially important differences based on ethnicity and/or age. If weighted back to their representation in the population, these important group differences may no longer be detected.

4. Power—The power of a statistical test is the probability that the test will correctly reject a false null hypothesis (i.e. detect a true effect). As with all statistical analyses, power increases as the sample size increases. Given the additional requirements of pattern-centered methods in terms of identifying subgroups rather than averaging across the population, these techniques require larger sample sizes than traditional approaches. As with traditional methods, base rates for the behavior of interest are also an important consideration. For example, while epidemiologic samples certainly offer generalizability and a necessary first step in mapping multiple etiologies, this goal may eventually require more targeted research designs. In that the majority of cases in any epidemiologic sample is not at risk for significant substance use and is exhibiting non problematic behaviors, it is likely that additional “high-risk” studies will be needed in order to uncover the heterogeneity of problematic pathways. For example, data from the Seattle Social Development Research Project following a cohort from grade 5 to young adulthood showed that 70% of the sample could be classified as non-binge drinkers, while only 4% of the sample exhibited any substantial or prolonged increases in their binge drinking behavior (Hill, White, Chung, Hawkins, & Catalano, 2000). In order to adequately examine the multiple etiologic processes likely at work in the development of substance use disorders, a new generation of research studies may be in order, sampled from an epidemiologic population, but screened to insure a concentration of cases that may elucidate heterogeneous pathways to and through problematic substance use outcomes. To date, not surprisingly, tobacco and alcohol use trajectories have been the most widely studied given their relatively high population base rates compared to other substances.

Model Selection

In trajectory analysis, selecting the appropriate model is accomplished by testing models with varying numbers of trajectories (usually between 2 and 8) and then using a combination of criteria for selecting a model that will be retained. These criteria include statistical fit (evaluated according to a deceleration in change in the Bayesian Information Criteria (BIC) across models with larger numbers of trajectories), likelihood of trajectory group membership for each participant (evaluated according to the average posterior probability index where an average value of .70 for all trajectory groups has been suggested as a minimum indicator of adequate model fit (Nagin, 2005)), and both parsimony and interpretability of the trajectories. In each model, individual trajectories are also tested to determine whether each is linear, quadratic or cubic in shape. For FGLM, using a combination of criteria including statistical fit, parsimony and interpretability of the trajectories, are also considered the most acceptable practices.

In contrast, for decision tree analyses, the primary focus of model selection is the avoidance of “overfitting” the data, a situation that arises when more and more splits (i.e. decision points) are added to the model that detract from the model’s generalizability when applied to new data not used to build the original model. To avoid this problem, decision tree models are first “grown” (i.e. a maximal number of splits or decision points are made in the data) until each resulting high and low risk groups with respect to the outcome of interest includes a small number of participants. All decision points in the data that do not reduce the predictive accuracy of the model (i.e. do not reduce the percentage of correct classification of participants with and without the outcome of interest) are then removed. There are many “pruning” techniques both within and across software packages that differ in the measurement that is used to optimize predictive accuracy of the model.

Conclusions

The goal of risk/protective factor research focusing on a wide variety of other substance outcomes is to inform the content and timing of efforts aimed at preventing the onset and/or

escalation of these conditions. Significant efforts in longitudinal research have been undertaken based on the belief that an understanding of processes involved in substance use initiation and escalation will provide the ground work for developing effective and cost efficient prevention strategies. While, pattern-centered theorizing about the development of substance use problems is common, the majority of statistical techniques used to evaluate the association between potential risk/protective factors and future substance use outcomes are variable-centered in that they include a general examination of interrelationships among variables (Bates, 2000) and commonly fail to characterize unique subpopulations that may be of interest in terms of etiology and/or treatment response. Thus, we have argued that pattern-centered methods have somewhat greater potential for informing targeted substance use intervention through the identification of homogenous subgroups that may be defined according to such characteristics as sequence, timing and developmental expression of both risk and outcome. Decisions on the specific type of pattern-centered approach to be used should be guided by such considerations as the type of research question (e.g. interest in time varying effects vs. an identification of early premorbid risk/protective factors), assumptions regarding the nature of the association (e.g. parametric vs. non-parametric), study design features (e.g. number of assessment waves) and available data (e.g. amount of missing data). It is important to add, however, that no statistical methods can be considered adequate for testing the complex and dynamic interplay between and among biological psychological and social factors involved in the development of substance use behaviors. As an iterative endeavor, substance use research as in all areas of science must inform complex theory from the building and integration of large numbers of empirical studies.

If multiple etiologies are truly at work in the population however, then further strides in the accurate prediction of substance use will likely be built on diverse pattern-centered approaches that explore the presence of multiple population subgroups across various substance use outcomes. The use of pattern centered methods with the potential to more directly test the complex interplay among established risk/protective factors have allowed empirical substance research to begin to move beyond the focus on static associations between variables and toward a more developmentally informed exploration of factors that may guide the process. Aside from addressing how empirical work can best identify real world etiologies for substance use disorder, the ultimate challenge will be to make this empirical work maximally informative to prevention. The continued development of statistical methods now underway will greatly assist in this process.

References

- Abroms L, Simons-Morton B, Haynie D, Chen R. Psychosocial predictors of smoking trajectories during middle and high school. *Addiction*. 2005; 100:852–861. [PubMed: 15918815]
- Audrain-McGovern J, Rodriguez D, Tercyak K, Cuevas J, Rodgers K, Patterson F. Identifying and characterizing adolescent smoking trajectories. *Cancer Epidemiology, Biomarkers & Prevention*. 2004; 13:2023–2034.
- Babor TF, Caetano R. Subtypes of substance dependence and abuse: implications for diagnostic classification and empirical research. *Addiction*. 2006; 101 Suppl. 1:104–110. [PubMed: 16930166]
- Babor, TF.; Del Boca, FK. *Treatment Matching in Alcoholism*. Cambridge, UK: Cambridge University Press; 2003.
- Bates ME. Integrating person-centered and variable-centered approaches in the study of developmental courses and transitions in alcohol use: Introduction to the special section. *Alcoholism: Clinical & Experimental Research*. 2000; 24(6):878–881.
- Bauer, DJ.; Shanahan, MJ. Modeling complex interactions: Person-centered and variable-centered approaches. In: Little, TD.; Bovaird, JA.; Card, NA., editors. *Modeling contextual effects in longitudinal studies*. Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers; 2007. p. 255-283.

- Bergman, LR.; von Eye, A.; Magnusson, D. Person-oriented research strategies in developmental psychopathology. In: Cicchetti, D.; Cohen, DJ., editors. *Developmental psychopathology: Theory and method*. 2 ed. Vol. 1. Hoboken, NJ: US: John Wiley & Sons Inc; 2006. p. 850-888.
- Bierman KL, Coie JD, Dodge KA, Foster EM, Greenberg MT, Lochman JE, et al. Fast track randomized controlled trial to prevent externalizing psychiatric disorders: Findings from grades 3 to 9. *Journal of the American Academy of Child & Adolescent Psychiatry*. 2007; 46(10):1250-1262. [PubMed: 17885566]
- Block J, Robins RW. A longitudinal study of consistency and change in self-esteem from early adolescence to early adulthood. *Child Development*. 1993; 64(3):909-923. [PubMed: 8339703]
- Botvin GJ, Griffin GW, Diaz T, Ifill-Williams M. Drug abuse prevention among minority adolescents: Posttest and one-year follow-up of a school-based preventive intervention. *Prevention Science*. 2001; 2(1):1-13. [PubMed: 11519371]
- Brieman, L.; Friedman, J.; Olshen, R.; Stone, C. *Classification and regression trees*. Pacific Grove, CA: US: Chapman & Hall; 1984.
- Brogan, D. Software for sample survey data: misuse of standard packages. In: Armitage, P.; Colton, T., editors. *Encyclopedia of Biostatistics*. 2 ed. Vol. 5. New York, New York: John Wiley & Sons, Inc; 2004. p. 4167-4174.
- Brown CH, Wang W, Kellam SG, Muthen BO, Petras H, Toyinbo P, et al. Methods for testing theory and evaluating impact in randomized field trials: Intent-to-treat analyses for integrating the perspectives of person, place, and time. *Drug and Alcohol Dependence*. 2008; 95:S74-S104. [PubMed: 18215473]
- Buettner CK, Bartle-Haring S, Andrews DW, Khurana A. Perceptions of alcohol policy and drinking behavior: Results of a latent class analysis of college student drinkers. *Addictive Behaviors*. 2010; 35(6):628-631. [PubMed: 20153587]
- Chassin L, Presson C, Pitts S, Sherman S. The natural history of cigarette smoking from adolescence to adulthood in a Midwestern community sample: Multiple trajectories and their psychosocial correlates. *Health Psychology*. 2000; 19:223-231. [PubMed: 10868766]
- Chung T, Maisto S, Cornelius J, Martin C, Jackson K. Joint trajectory analysis of treated adolescents' alcohol use and symptoms over 1 year. *Addictive Behaviors*. 2005; 30:1690-1701. [PubMed: 16098681]
- Chung T, Maisto SA, Cornelius JR, Martin CS, Jackson KM. Joint trajectory analysis of treated adolescents' alcohol use and symptoms over 1 year. *Addictive Behaviors*. 2005; 30(9):1690-1701. [PubMed: 16098681]
- Cicchetti D, Rogosch FA. Equifinality and multifinality in developmental psychopathology. *Development and Psychopathology*. 1996; 8(4):597-600.
- Colder C, Mehta P, Balanda K, Campbell R, Mayhew K, Stanton W, Pentz W, Flay B. Identifying trajectories of adolescent smoking: An application of latent growth mixture modeling. *Health Psychology*. 2001; 20:127-135. [PubMed: 11315730]
- Collins, L.; Lanza, S. *Latent Class and Latent Transition Analysis: for applications in the social, behavioral and health sciences*. Hoboken, NJ: John Wiley & Sons, Inc; (in press)
- Collins LMG, John W. The effect of timing and spacing of observations in longitudinal studies of tobacco and other drug use: Temporal design considerations. *Drug and Alcohol Dependence*. 2002; 68 Suppl1:S85-S96. [PubMed: 12324177]
- Costello DM, Dierker LC, Jones BL, Rose JS. Trajectories of smoking from adolescence to early adulthood and their psychosocial risk factors. *Health Psychology*. 2008; 27(6):811-818. [PubMed: 19025277]
- Dierker L, Lloyd-Richardson E, Stolar M, Flay B, Tiffany S, Collins L, Bailey S, Nichter M, Nichter M, Clayton R. TERN. The proximal association between smoking and alcohol use among first year college students. *Drug and Alcohol Dependence*. 2006; 81(1):1-9. [PubMed: 16006056]
- Dierker LC, Avenevoli S, Goldberg A, Glantz M. Defining subgroups of adolescents at risk for experimental and regular smoking. *Prevention Science*. 2004; 5(3):169-183. [PubMed: 15470937]
- Feelders, AJ. *Handling Missing Data in Trees: Surrogate Splits or Statistical Imputation*; Paper presented at the Proceedings of the Third European Conference on Principles of Data Mining and Knowledge Discovery; 1999.

- Freedman M, Lester K, McNamara C, Milby J, Schumacher J. Cell phones for ecological momentary assessment with cocaine-addicted homeless patients in treatment. *Journal of Substance Abuse Treatment*. 2006; 30(2):105–111. [PubMed: 16490673]
- Guo J, Chung I, Hill K, Hawkins D, Catalano R, Abbott R. Developmental relationships between adolescent substance use and risky sexual behavior in young adulthood. *Journal of Adolescent Health*. 2002; 31:354–362. [PubMed: 12359381]
- Hildebrandt T, Langenbucher JW, Carr SJ, Sanjuan P. Modeling population heterogeneity in appearance- and performance-enhancing drug (APED) use: Applications of mixture modeling in 400 regular APED users. *Journal of Abnormal Psychology*. 2007; 116(4):717–733. [PubMed: 18020718]
- Hill KG, White HR, Chung I-J, Hawkins J, Catalano RF. Early adult outcomes of adolescent binge drinking: Person- and variable-centered analyses of binge drinking trajectories. *Alcoholism: Clinical & Experimental Research*. 2000; 24(6):892–901.
- Hopper JW, Su Z, Looby AR, Ryan ET, Penetar DM, Palmer CM, et al. Incidence and patterns of polydrug use and craving for ecstasy in regular ecstasy users: An ecological momentary assessment study. *Drug and Alcohol Dependence*. 2006; 85(3):221–235. [PubMed: 16730923]
- Hu M-C, Muthén B, Schaffran C, Griesler PC, Kandel DB. Developmental trajectories of criteria of nicotine dependence in adolescence. *Drug and Alcohol Dependence*. 2008; 98:94–104. [PubMed: 18602225]
- Jackson KM, Sher KJ, Wood PK. Trajectories of concurrent substance use disorders: A developmental, typological approach to comorbidity. *Alcoholism: Clinical & Experimental Research*. 2000; 24(6):902–913.
- Jester J, Nigg J, Buu A, Puttler L, Glass J, Heitzeg M, et al. Trajectories of childhood aggression and inattention/hyperactivity: Differential effects on substance abuse in adolescence. *Journal of the American Academy of Child and Adolescent Psychiatry*. 2008; 47:1158–1165. [PubMed: 18724257]
- Jones BL, Nagin D. Advances in group-based trajectory modeling and an SAS procedure for estimating them. *Sociological Methods and Research*. 2007; 35:452–571.
- Jones B, Nagin D, Roeder K. A SAS procedure based on mixture models for estimating developmental trajectories. *Sociological Methods and Research*. 2001; 29:384–393.
- Jung T, Wickrama KAS. An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling. *Social and Personality Psychology Compass*. 2008; 2(1):302–317.
- Kumpfer, KL.; Alvarado, R.; Tait, C.; Whiteside, HO. The Strengthening Families Program: An evidence-based, multicultural family skills training program. In: Tolani, P.; Szapocznik, J.; Sambrano, S., editors. *Preventing youth substance abuse: Science-based programs for children and adolescents*. Washington, DC: US: American Psychological Association; 2007. p. 159–181.
- Labouvie EW, Pandina RJ, Johnson V. Developmental trajectories of substance use in adolescence: Differences and predictors. *International Journal of Behavioral Development*. 1991; 14(3):305–328.
- Lemon SC, Roy J, Clark MA, Friedmann PD, Rakowski W. Classification and regression tree analysis in public health: Methodological review and comparison with logistic regression. *Annals of Behavioral Medicine*. 2003; 26(3):172–181. [PubMed: 14644693]
- Lessov-Schlaggar CN, Hops H, Brigham J, Hudmon KS, Andrews JA, Tildesley E, et al. Adolescent smoking trajectories and nicotine dependence. *Nicotine & Tobacco Research*. 2008; 10(2):341–351. [PubMed: 18236299]
- Li F, Duncan T, Duncan S, Hops H. Using Piecewise Growth Mixture Modeling of Adolescent Alcohol Use Data. *Structural Equation Modeling*. 2001; 8:175–204.
- Li F, Duncan TE, Hops H. Examining developmental trajectories in adolescent alcohol use using piecewise growth mixture modeling analysis. *Journal of Studies on Alcohol*. 2001; 62(2):199–210. [PubMed: 11327186]
- Li, R.; Root, T.; Shiffman, Saul. A Local Linear Estimation Procedure for Functional Multilevel Modeling. In: Walls, TA.; Schafer, JL., editors. *Models for intensive longitudinal data*. New York, NY: US: Oxford University Press; 2006. p. 63–83.

- Maldonado-Molina MM, Collins LM, Lanza ST, Prado G, Ramirez R, Canino G. Pattern of substance use onset among Hispanics in Puerto Rico and the United States. *Addictive Behaviors*. 2007; 32(10):2432–2437. [PubMed: 17493764]
- Magnusson, D.; Stattin, H. The Person in Context: A holistic-interactionistic Approach. In: Lerner, RM.; Damon, W., editors. *Handbook of child psychology: Theoretical models of human development*. 6 ed. Vol. 1. Hoboken, NJ: US: John Wiley & Sons Inc; 2006. p. 400-464.
- McKenzie DP, McFarlane AC, Creamer M, Ikin JF, Forbes AB, Kelsall HL, et al. Hazardous or harmful alcohol use in Royal Australian Navy veterans of the 1991 Gulf War: Identification of high risk subgroups. *Addictive Behaviors*. 2006; 31(9):1683–1694. [PubMed: 16460884]
- Miyazaki Y, Raudenbush S. Testing for linkage of multiple cohorts in an accelerated longitudinal design. *Psychological Methods*. 2000; 5:44–63. [PubMed: 10937322]
- Muthén B, Muthén L. Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*. 2000; 24:882–891.
- Muthén B, Shedden K. Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrics*. 1999; 55:463–469. [PubMed: 11318201]
- Muthén, LK.; Muthén, BO. *Mplus User's Guide*. 5 ed.. Los Angeles, CA: 1998–2007.
- Nagin, D. *Group-based modeling of development*. Cambridge, MA: US: Harvard University Press; 2005.
- Orlando M, Tucker J, Ellickson P, Klein D. Developmental trajectories of cigarette smoking and their correlates from early adolescence to young adulthood. *Journal of Consulting and Clinical Psychology*. 2004; 72:400–410. [PubMed: 15279524]
- Schafer JL, Graham JW. Missing data: Our view of the state of the art. *Psychological Methods*. 2002; 7(2):147–177. [PubMed: 12090408]
- Schulenberg J, O'Malley PM, Bachman JG, Wadsworth KN, Johnston LD. Getting drunk and growing up: Trajectories of frequent binge drinking during the transition to young adulthood. *Journal of Studies on Alcohol*. 1996; 57(3):289–304. [PubMed: 8709588]
- Segal MR. Tree structured methods for longitudinal data. *Journal of the American Statistical Association*. 1992; 87(418):407–418.
- Shedden K, Zucker RA. Regularized finite mixture models for probability trajectories. *Psychometrika*. 2008; 73(4):625–646. [PubMed: 19956348]
- Shiffman S, Balabanis MH, Gwaltney CJ, Paty JA, Gnys M, Kassel JD, et al. Prediction of lapse from associations between smoking and situational antecedents assessed by ecological momentary assessment. *Drug and Alcohol Dependence*. 2007; 91(2–3):159–168. [PubMed: 17628353]
- Stanton W, Flay B, Colder C, Mehta P. Identifying and predicting adolescent smokers' developmental trajectories. *Nicotine & Tobacco Research*. 2004; 6:843–852. [PubMed: 15700920]
- Steinberg, D.; Golovnya, M. *CART: Users Guide*. San Diego, CA: US: Salford Systems; 2007.
- Swan GE, Javitz HS, Jack LM, Curry SJ, McAfee T. Heterogeneity in 12-month outcome among female and male smokers. *Addiction*. 2004; 99(2):217–250.
- Vik PW, Cellucci T, Hedt J, Jorgensen M. Transition to college: A classification and regression tree (CART) analysis of natural reduction of binge drinking. *International Journal of Adolescent Medicine and Health*. 2006; 18(1):171–180. [PubMed: 16639871]
- Walls, TA.; Schafer, JL., editors. *Models for intensive longitudinal data*. New York, NY: US: Oxford University Press; 2006.
- White, HR.; Bates, ME.; Labouvie, E. Adult outcomes of adolescent drug use: A comparison of process-oriented and incremental analyses. In: Jessor, R., editor. *New perspectives on adolescent risk behavior*. New York, NY: US: Cambridge University Press; 1998. p. 150-181.
- White HR, Pandina RJ, Chen P-H. Developmental trajectories of cigarette use from early adolescence into young adulthood. *Drug & Alcohol Dependence*. 2002; 65(2):167–178. [PubMed: 11772478]
- Witkiewitz K, Masyn K. Drinking trajectories following an initial lapse. *Psychology of Addictive Behaviors*. 2008; 22:157–167. [PubMed: 18540713]
- Zhang, H.; Singer, B. *Recursive Partitioning in the Health Science*. New York: Springer; 1999.

Figure 1.
Hypothetical Trajectories of Smoking Behavior (Growth Mixture Modeling)

Figure 2.
Hypothetical Trajectories of Smoking Behavior (Functional Hierarchical Linear Modeling)

Figure 3.
Hypothetical Tree Diagram for Alcohol Abuse

Table**Comparison of Pattern-Centered Methods**

	Trajectory Analysis	FHLM	Decision Tree
Outcome	Binary Count Ordered	Binary Count Ordered	Binary Count
Predictors	Binary Count Ordered Time stable	Binary Count Ordered Both time stable and time varying	Binary Count Ordered Time stable
Covariates	Time stable and time varying	Similar to predictors above	Similar to predictors above
Missing Data	Includes cases with missing data on the outcome measure and on time-varying predictors. Drops cases with missing data on one or more time stable predictors	Includes cases with missing data on the outcome measure, Drops cases with missing data on one or more predictors	Drops cases with missing data on the outcome measure. Includes cases with missing data on one or more predictors
Number of Waves	3 +	50 +	1 to 2
Spacing of Waves	Even or uneven	Even or uneven	--
Assumptions	Population heterogeneity results from multiple homogenous subgroups Shape of trajectory Distribution of the outcome Repeated measure covariance structure Logistic regression model links group membership probability to predictors; linear relationship between time-stable covariates and outcome	Population heterogeneity results from multiple homogenous subgroups Distribution of the outcome Repeated measure covariance structure Relationship between outcome and covariates allowed to change over time instead of being constant over the course of trajectory	None