Published in final edited form as:
J Abnorm Psychol. 2011 May ; 120(2): 322–335. doi:10.1037/a0021813.

Alcohol Use Trajectories and the Ubiquitous Cat's Cradle: Cause for Concern?

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Abstract

In recent years, trajectory approaches to characterizing individual differences in the onset and course of substance involvement have gained popularity. Previous studies have sometimes reported four prototypic courses: (1) a consistently "low" group, (2) an "increase" group, (3) a "decrease" group, and (4) a consistently "high" group. Although not always recovered, these trajectories are often found despite these studies varying in the ages of the samples studied and the duration of the observation periods employed. We examined the consistency with which these longitudinal patterns of heavy drinking were recovered in a series of latent class growth analyses that systematically varied the age of the sample at baseline, the duration of observation, and the number and frequency of measurement occasions. Data were drawn from a four-year, eight-wave panel study of college student drinking (N=3720). Despite some variability across analyses, there was a strong tendency for these prototypes to emerge regardless of the participants' age at baseline and the duration of observation. These findings highlight potential problems with commonly employed trajectory-based approaches and the need to not over-reify these constructs.

Historically, alcohol researchers have classified different types of problematic alcohol use on factors related to personal characteristics such as age-of-onset, gender, family history of alcoholism, personality traits, and comorbid psychopathology (e.g., Babor, 1996; Babor et al., 1992; Cloninger, 1987). One dimension that has been featured prominently in relatively recent classifications is that of developmental course (Zucker, 1987; Zucker, 1994; Zucker, Fitzgerald, & Moses, 1995). A rapidly evolving body of work has used various types of categorical trajectory-based approaches to model change in alcohol consumption, alcohol-related problems, and alcohol use disorders (Bennett, McCrady, Johnson, & Pandina, 1999; Casswell, Pledger, & Pratap, 2002; Chassin, Flora, & King, 2004; Chassin, Pitts, & Prost, 2002; Chung, Maisto, Cornelius, & Martin, 2005; Chung, Maisto, Cornelius, Martin, & Jackson, 2005; Colder, Campbell, Ruel, Richardson, & Flay, 2002; D'Amico et al., 2001; Feldman, Masyn, & Conger, 2009; Flory, Lynam, Milich, Leukefeld, & Clayton, 2004; Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005; Guo et al., 2002; Hill, White,

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Chung, Hawkins, & Catalano, 2000; Jackson & Sher, 2005; Jackson & Sher, 2006; Jackson & Sher, 2008; Jackson, Sher, & Schulenberg, 2008; Jacob, Bucholz, Sartor, Howell, & Wood, 2005; Johnsson, Leifman, & Berglund, 2008; Martino, Ellickson, & McCaffrey, 2009; Mitchell & Beals, 2006; Muthén & Muthén, 2000; Oesterle et al., 2004; Schulenberg, Wadsworth, O'Malley, Bachman, & Johnston, 1996b; Schulenberg, O'Malley, Bachman, Wadsworth, & Johnston, 1996a; Toumbourou, Williams, Snow, & White, 2003; Tucker, Orlando, & Ellickson, 2003; Tucker, Ellickson, Orlando, Martino, & Klein, 2005; Van Der Vorst, Vermulst, Meeus, Deković, & Engels, 2009; Wanner, Vitaro, Ladouceur, Brendgen, & Tremblay, 2006; White, Johnson, & Buyske, 2000; Warner, White, & Johnson, 2007; Weisner, Weichold, & Silbereisen, 2007; Windle, Mun, & Windle, 2005; Witkiewitz & Masyn, 2008). Within each study, the groups (or classes) characterizing distinct developmental trajectories (typically, though not always, based upon slope-intercept growth models) generally vary as a function of level at the initial stage being studied (i.e., intercept) and the magnitude and direction of change (i.e., slope). For the most part, several broad classes of trajectories have consistently emerged: a low or non-using trajectory ("low"), a chronic/persistently high use trajectory ("high"), a trajectory marked by high use that gradually declines over the timespan ("decrease"), and a trajectory marked by low use that gradually increases over the timespan ("increase"). Not unexpectedly, trajectories derived from young and mid-adolescent samples tend to detect one or more courses typified by escalation but not necessarily a decreasing course, whereas samples that span young adulthood are likely to reveal a decreasing course. That is, in very youthful samples, there are many abstainers and few regular users. Thus, there is virtually no opportunity to observe declining trajectories. Similarly, in older samples that begin observations after the period of risk for onset, there is less opportunity to observe increasing trajectories. In addition, small group of studies also have identified a "fling" or "time-limited" trajectory (e.g., Martino et al., 2009; Schulenberg et al., 1996a; 1996b; Windle et al., 2005) or a trajectory with moderate levels of alcohol involvement that fall midpoint between the high and low groups (e.g., Casswell et al., 2002; Colder et al., 2002; Tucker et al., 2005; Van Der Vorst et al, 2009).

Within the logical constraints just described, the frequent detection of four general trajectory patterns (chronic high, increasing, decreasing, and non/low using courses) is seemingly robust to the age of the sample (i.e., where the intercept is set), the measure of alcohol involvement (also see Jackson & Sher, 2005), and the length of observation (Jackson & Sher, 2006). To illustrate this phenomenon, we identified several studies that differ along these dimensions (i.e., different ages, measures, and study duration) but whose trajectories of alcohol involvement evince the characteristic four-class pattern.[1] Some of these studies identified trajectories based on alcohol consumption that spanned adolescence (Colder et al., 2002; Feldman et al., 2009; Toumboreau et al. 2003; Weisner et al., 2007) or young adulthood (Jackson & Sher, 2005; Schulenberg et al., 1996), and one study, which modeled alcohol dependence diagnoses, covered the whole span of adulthood (Jacob et al., 2005). Two studies characterized trajectories over a single year, with one study modeling abstinence in an adolescent clinical sample (Chung et al., 2004) and another study examining drinks per week using a sample of college freshman (Greenbaum et al., 2005). We selected five of these studies and charted these trajectories in a single figure (see Figure 1) to illustrate an interesting but conceptually troubling phenomenon. That is, we sometimes observe a consistent pattern that includes groups with (1) a high and flat slope, (2) a decreasing slope, (3) an increasing slope, and (4) a low and flat slope. This pattern is reminiscent of the child's game "cat's cradle," in particular, what is known as the soldier's bed variant (Jayne, 1962; see Figure 2). Although there is some degree of variation in the

[1]For the most part, the remaining studies on alcohol trajectories have identified three of these four patterns.

intercept in these models, the similarities are striking and raise a perplexing question: Why do we often observe similarly looking trajectories despite the fact that we are looking at individuals at different stages of life and observed for different periods of time?

In Figure 3, the top two panels and the lower left panel illustrate the soldier's bed cat's cradle pattern of varying duration and at varying points in the life course. As illustrated in Figure 1, there is evidence for these three patterns even though the “long” pattern (lower left panel) is logically inconsistent with the “shorter” patterns (in the two top panels). Additionally, we have not found evidence for what we've termed “the missing “diamond back” (Figure 3 lower right panel) and related patterns that are the logical outcome of adjoining the patterns in the two adjacent, “shorter” patterns in the top two panels.

The difficulties in attempting to characterize trajectories, even if there were no anomalies in data or analytic approach are illustrated in Figure 4. In panel A, we portray five distinct hypothetical trajectories: (1) a low use trajectory over the life course, (2) a short course that begins early, (3) a short course that begins somewhat later, (4) a long course that begins early, and (5) a long course that begins somewhat later. Consideration of even this small set of possibilities illustrates a number of potential problems of substantive interpretation of trajectories, in general. For example, is it more important to distinguish chronicity or onset or do both need to be considered? Perhaps most critical, and illustrated in panels B-F, is that our ability to distinguish among these “true” trajectories is severely limited by our observation window. For example, the observation window in panel B might yield three patterns: (1) low use, (2) earlier onset, and (3) the beginning of an earlier onset. In panel C, we would be able to differentiate short and long courses with early onset but not among later onset courses. In panel D, we see a soldier's bed cat's cradle. In panel E, we would observe a cat's cradle plus a “fling” (Schulenberg et al., 1996a) trajectory. Finally, in panel F, we'd see two recovery classes based on when recovery starts to occur. The extant literature on drinking (and related trajectories) fails to consider the underlying life course patterns that might be generating observed intermittent patterns that result from observation periods that are invariably right censored and very often left censored. In the criminology literature on offending, the importance of length of follow-up on the nature and number of trajectories recoverd has been convincingly documented (Eggleston, Laub, & Sampson, 2004), adding further weight to our conceptual analysis that is illustrated in Figure 4.

Beyond this general concern, the seeming ubiquity of the soldier's bed “cat's cradle” raises serious concerns about the meaning and utility of various trajectory-based approaches currently in use. If we frequently uncover these four classes (with or without an additional class that is sometimes observed) does it tell us more about the biases inherent in our analytic approach as opposed to the underlying phenomenon we are attempting to describe? Unfortunately, our noticing that the same patterns frequently emerge from studies differing in participant age and duration of observation is difficult to interpret. Perhaps the biggest challenge to interpretation is that these studies vary not only in initial (baseline) ages of samples and duration (and number) of observations, but in a variety of other ways (e.g., population sampled, ascertainment strategy, recruitment success, measures employed) that could confound direct comparisons.

Overview

We believe that this pattern, while certainly not inevitable or invariant, occurs with enough frequency in the alcohol trajectory literature to justify further examination in a dataset with a sufficiently long observation period and number of observations that would permit systematic modeling of the effects of both baseline age and duration of observation. Using data from a four-year prospective study on a single-cohort college student sample, we created a series of permutations which varied the length of the observation and the intercept (initial sample age). We limited our examination to a single measure, heavy episodic drinking, for didactic purposes and given its relevance to college student alcohol involvement (Wechsler & Nelson, 2001). The present study builds on our program of research investigating methodological factors that are critical to characterizing the developmental course of alcohol involvement (Jackson & Sher, 2005; 2006; 2008).

Method

Participants and Procedure

Participants were 3,720 entering first-time college students from a large Midwestern university (see Sher & Rutledge, 2007). The sample was 54% female, 90% white, non-Hispanic, and the mean age was 18.6 years (SD=0.36). Participants completed a paper-and-pencil baseline survey during a campus-based freshman group summer orientation session. They were re-contacted in the fall (regardless of enrollment status) and were invited to participate in a series of web-based assessments that took place during each semester. Because 289 (7.8%) respondents participated only at the pre-college assessment and 373 (10.0%) participated only in one wave, we restricted the sample to those participants who completed at least two waves of the college assessment. Additionally, lifetime abstainers were excluded. These participants (N=3,058; 58% female, 90.4% white, non-Hispanic, mean age of 17.9 years) were similar to the pre-college sample with respect to ethnicity and age but were slightly more likely to be female (58% vs. 54%).

Measures

Heavy drinking—Frequency of heavy episodic drinking was assessed at each wave with an item which inquired about the number of times in the past 30 days the participant had consumed five or more drinks in a row at a single sitting. The item had eight response options: 0=Did not in past 30 days; 1=Once in past 30 days; 2=2-3 times in past 30 days; 3=Once or twice a week; 4=3-4 times a week; 5=5-6 times a week; 6=Nearly every day; 7=Every day; 8=Twice a day or more. From this item, a binary heavy drinking variable was computed, with consumption of 5+ drinks in the past 30 days on at least one occasion coded as 1 and no heavy drinking in the past 30 days coded as 0.[2]

Analytic Approach

To extract trajectories of heavy drinking, we conducted growth mixture models. We estimated eight models that included the full assessment period (Waves 1-8) as well as models restricted to Waves 1-7, Waves 1-6, Waves 1-5, Waves 1-4, Waves 5-8, Waves 1, 3, 5, and 7, and Waves 2, 4, 6, and 8. Growth mixture modeling (Muthén, 2001; Muthén & Shedden, 1999; Nagin, 1999) models variability in growth with a latent categorical variable that corresponds to homogeneous groups of individuals who have similar patterns of alcohol use. The underlying latent growth model was parameterized with intercept and linear and quadratic[3] slope growth factors (slope factor loadings were set according to the interval between assessments) and used a logit link to model the categorical manifest variables.

Classes were identified based on the mean of the growth factors alone, assuming no variation across individuals within a class (Nagin, 1999). This approach also has been

[2]This coding was done to facilitate model convergence, which was challenging when data were treated as ordered categories. Our initial attempt was to model it as a five-level ordinal variable was abandoned when the model was still iterating after a week, which is due to the intensive numeric integration for ordinal outcomes. We also ran the models treating HED as continuous variables, but several models (Wave 1-4, Waves 5-8, and Waves 2, 4, 6, and 8) resulted in a non-positive definite covariance matrix for the three-class model. Given the goal of the paper, we then decided to go with the simplest modeling procedure (i.e., two-level outcome, no estimation of within-class variance).

referred to as latent class growth analysis (LCGA).[4] Models were estimated using Mplus Version 5.10 (Muthén & Muthén, 1998-2007). Models were run with automatically generated random start values with up to 5000 initial-stage random sets of starting values and 500 final stage optimizations (several models failed to converge with fewer sets of start values and fewer optimizations). Because retention rates for any one follow-up survey averaged 75%-80%, models were run using full information maximum likelihood, which assumes data are missing at random.

Results

Trajectory Identification

Because the goal of the present study was to examine the characteristic four-class pattern, we first focused on the four-class solution for all seven models, which permitted us to make meaningful comparisons. Figure 5 depicts estimated mean growth trajectories for heavy alcohol use by trajectory class across the different models.[5] In all cases, the groups include a chronic non- or low group (ranging from 21% to 35%), a chronic high group (from 34% to 47%), a decreasing (developmentally limited) group (from 3% to 30%), and an increasing (late-onset) group (from 3% to 27%). For all models, we observe variations on the characteristic “cat's cradle” with a low group, a high group, an increase group, and a decrease group. However, the patterns observed in the Wave 1 – Wave 4 (Figure 5e) and the Waves 2, 4, 6, 8 (Figure 5g) models appear least prototypic and the pattern observed in the Wave 1 – Wave 8 model (Figure 5a) the most prototypic. Indeed, in the Wave 1 – Wave 4 model, it could be argued that rather than observing a decrease group we observed a relatively stable, moderate group. It is instructive that the increase class asymptotes at Wave 3 for the Wave 1 – Wave 4 model but at Wave 7 for the Wave 1 – Wave 8 model, highlighting variation across models and suggesting that despite the general tendency for the four-class soldier's bed pattern to emerge, the shape of individual trajectories are somewhat conditional upon the number of observations and duration of the observation period.

To determine whether the same participants tended to be placed in similar groups across different models, we estimated agreement statistics to characterize the consistency of classification (see Table 1). Overall, agreement in classification across the different models was quite good: using the Hubert-Arabie adjusted Rand index (Hubert & Arabie, 1985;Steinley, 2004), a measure of association that represents the degree of agreement between two separate partitions (i.e., clusterings) of the data, agreement ranged from .34 to .88 (see upper diagonal). Based on Cohen's (1960) κ, agreement ranged from .40 to .90 across the pairwise comparisons (see lower diagonal). In one sense these findings are somewhat reassuring in that they suggest that if someone is interested in categorizing individuals, the start point, number of observations, and duration of observation may be less critical than one might superficially assume. It is also reassuring that the lowest agreement occurred between the Wave 1 – Wave 4 model and the Wave 5 – Wave 8 model which did not have any measurement occasions in common and did not overlap temporally. However, it could be that this agreement is largely driven by overall level (or intercept) or unmodeled

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[3]We might expect more elaborate patterns when higher-order polynomials are modeled, so an ancillary set of models was modeled with a cubic slope factor. When models with cubic terms converged for the four-class solution, all models exhibited the characteristic cat's cradle; the four-class solution failed to converge for the models using Waves 1-4, Waves 1, 3, 5, and 7, and Waves 2, 4, 6, and 8. In addition, LCGA treats time as an ordered variable (by virtue of setting slope factor loadings according to the interval between assessments). It is also possible to treat each timepoint as an unordered variable without specifying a slope, such as in a latent class analysis (LCA). However, one advantage of LCGA over LCA is the need in LCA to impose constraints to achieve model identification, as is the case when estimating even a three-class solution with four timepoints (McCutcheon, 1987).

[4]In practice, permitting variation around the group mean results in a far more complex model (Nagin & Tremblay, 2005) and relaxing this assumption frequently results in greater likelihood of encountering convergence problems, consistent with other studies using this approach.

[5]The set of models were also estimated using listwise deletion. Findings were nearly identical to those using missing data.

trait-like variables and that relatively little additional information is obtained with the trajectory class information. Overall, findings suggest that we can be confident in the reliability of class as a function of similarities in ages and duration of measurement occasion. However, even when there are no measurement occasions in common (and no temporal overlap) as with the Waves 1-4 versus Waves 5-8 models, we still have modest agreement.

The comparison of the Waves 1-4, Waves 5-8, and Waves 1-8 solutions (see Figure 6) is especially informative in illustrating the discontinuities across solutions of various lengths and starting points. Although we see variants of the soldier's bed in all three solutions, it would be difficult to deduce the form of the solution based on all measurement occasions from the solutions based upon either the first half or the second half of the series. Indeed, we find the comparison of solutions highlighted in Figure 6 to be especially troubling in that it starkly illustrates the lack of relationship between solutions based on parts and the whole and how parochial a given time-bounded solution is. Specifically, the observed divergence between the spliced together classes derived from Waves 1-4 and Waves 5-8 when compared to those derived directly from Waves 1-8 results, in the very least, a logical inconsistency. Namely, one would expect that, if the behavior being modeled followed a static pattern, then regardless of where a “slice” of the time-course was taken, the modeled data should fall on (or near to) the trajectories obtained from modeling the data as a whole.

To probe this issue further, we examined how various combinations of “cat's cradle” patterns based on Waves 1-4 and on Waves 5-8 are represented in Waves 1-8 models. In this way, we can empirically demonstrate how seeming logical inconsistencies are manifested in analyses based upon a consideration on temporally adjacent classes derived from parallel sets of analyses on earlier versus later observations and their relation to the entire data series (i.e., Waves 1-8). Figure 7 illustrates the findings from this set of analyses. Specifically, we first estimated the Wave 1-4 cat's cradle trajectories (see the rows of the figure) and cross-tabulated these with the Wave 5-8 trajectories (see the columns of the figure). Thus, all 16 combinations derived from the Wave 1-4 cat's cradle and the Wave 5-8 are represented.

For example, in the first cell (i.e., comparing “chronics” in the Wave 1-4 with “chronics” in the Wave 5-8 analysis), we see that the overwhelming majority of these individuals are recovered in the Wave 1-8 chronic group (986 out of 991; with only 2 individuals showing a “decrease” pattern and three individuals showing an “increase” pattern). When we consider the other logically consistent pattern, the nonbingers from Wave 1-4 and the nonbingers from Wave 1-5, the consistency of results with the Wave 1-8 analysis is perfect (all 539 participants are classified as nonbingers in the Wave 1-8 analysis). Thus, individuals who are classified as either stably chronic or stably nonbingeing in both Wave 1-4 and Wave 5-8 analyses are almost certainly classified similarly in the Wave 1-8 analysis.

However, when we move from combining temporally adjacent groups that are either stably chronic or stably nonbingeing, we introduce varying levels of logical inconsistency which we might consider as either mild inconsistency (e.g., nonbingeing with increasing, chronic with decreasing, increasing with decreasing, decreasing with increasing) or large inconsistency (e.g., increasing with increasing, decreasing with decreasing). It is these configurations that hold potential for probing the meaning of trajectories based upon truncated observation periods and their longitudinal consistency.

Focusing on two of the “large inconsistency” combinations illustrates our concerns. For example, the 42 participants who manifest decreasing Wave 1-4 trajectories with decreasing Wave 5-8 trajectories shows both a decreasing trajectory (n=18) and an *increasing* trajectory (n=24) but with no chronic or non-bingeing patterns in the Wave 1-8 analyses. Similarly, the 81 participants who showed Wave 1-4 chronic trajectories and Wave 5-8 increasing trajectories tend to be classified as decreasing (*n*=49) but also as increasing (*n*=15) and chronic (*n*=17) in the Wave 1-8 analyses. Examining these and other configurations highlights the point that temporally adjacent longitudinal trajectories do not reliably identify specific longer term trajectories when based on the entire observation period. More generally, it is hazardous to attempt to generalize from either increasing or decreasing classes from shorter observation periods (Waves 1-4, Waves 5-8) to a longer observation periods. As illustrated in the row and column marginal comments in Figure 7, only a minority of individuals with patterns classified as increasing or decreasing over four waves are similarly classified over eight waves. This is in contrast to the situation with stable patterns where over 80% of individuals with chronic and nonbingeing patterns over four adjacent waves were similarly classified when the entire observation was considered. Unfortunately, it is typically the unstable, later-onset or desisting groups that are of greatest interest from a developmental perspective.

To evaluate whether the four-class pattern is just a simplification of a solution that in reality is best characterized by a larger number of classes, we estimated models solutions for greater than four classes (see Table 2). When possible, we estimated models for up to seven classes. According to the Bayesian Information Criterion, BIC (Schwarz, 1978) and a likelihood ratio test for relative improvement in fit, the Vuong-Lo-Mendell-Rubin test (VLMR; Lo, Mendell & Rubin, 2001), we concluded that the four-class solution was best for all models except the Wave 1 – Wave 8 model, although the BIC favored the three-class solution for the Waves 1-4, Waves 1-5, and Waves 2, 4, 6, and 8 models (with the three-class solution corresponding to low, moderate, and high drinking trajectories). However, in these three cases, the VLMR test suggested that an additional class was needed. For the Wave 1 – Wave 8 model, the five-class solution was best-fitting; for this model, the increase class was split into two increase classes, distinguished by a high versus low intercept (with one intercept roughly at zero and the other roughly at 0.35) but virtually identical slopes. We would argue that this additional class would conceptually be interpreted as supporting the increase pattern in the cat's cradle prototype. It is important to note, however, that the five-class (and greater) solutions would not converge for the Wave 5 – Wave 8 model, and many of the five-class solutions required that parameters be fixed to avoid singularity in the information matrix. Thus, these findings indicate a highly consistent four-class pattern regardless of the length of the observation and the intercept (sample age), and suggest that the four-class solution is not merely a simplification of a more complex model with more than four classes.

Discussion

Many researchers have embraced person-centered, categorical trajectory-based approaches such as longitudinal latent class analysis and growth mixture modeling for studying developmental variations in the course of alcohol and other forms of substance involvement because it offers the opportunity to characterize distinct subgroups of individuals who appear to show meaningful variation in their substance involvement as they age. Researchers have long theorized that there are various forms of alcoholism and some of these theories imply different trajectories with respect to age of onset and rate of escalation (Babor, 1996). Zucker's (1987) proposed typology explicitly classified different forms of alcoholism based on trajectories of use and related problems (as well as comorbidity) well before empirical studies of trajectories started to appear in the literature. He and other theorists based their typologies on existing clinical and nonclinical studies that identified these noteworthy differences in course. Clearly, there can be little doubt that there are meaningful differences in the course of various forms of substance involvement. The question we are attempting to address here is whether we can be confident that the standard approaches currently being employed in the literature can reliably resolve these variations in course in a way that is highly generalizable and not overly dependent upon a specific study design and analytic approach.

This question arose because we became skeptical of the appearance of the cat's cradle in our and others' work, and the problem it posed when one considered that similar patterns were being observed in studies that varied in the baseline ages of samples studied and length of the observation period employed. Why should a one-year study (e.g., Chung et al., 2004; Greenbaum et al., 2005), a four-year study (e.g., Weisner et al., 2007; the current study), and a 20-year study (Jacob et al., 2005) all yield soldier's bed patterns unless there is something about the analytic techniques themselves, the assumptions that go into the application of the techniques, or more subtle variations in parameterizing models. We have previously investigated how a variety of variables, including index of alcohol involvement, number and timing of assessment occasions, and different severities or thresholds of measurement (Jackson & Sher, 2005, 2006, & 2008), affect the nature of trajectories obtained and have concluded that the discrete classes of alcohol use observed using these techniques do not, as Plato put it “carve nature at her joints” (to borrow a phrase used by Gangestad & Snyder, 1985). Our current investigation is different than those previous efforts in that here we try to establish how various aspects of design affect the likelihood of obtaining a specific pattern, the soldier's bed variant of the cat's cradle, which is often found in studies that differ in ways that should logically produce different patterns of trajectories rather than the same one.

Our empirical findings from this sample provided some support for the robustness of the cat's cradle in that regardless of our start point or length of observation, we tended to find four groups that could be described as an increasing group, a decreasing group, a consistently low group, and a consistently high group. Although this basic pattern was preserved across different models, it varied considerably from the prototype that we observed across eight waves spanning four years (and that others have found in different age samples spanning different lengths of time; see Figure 1) to more marginal instantiations of it in some of our models. Moreover, many published studies have not reported the soldier's bed pattern and it's not yet clear what substantive, methodological, and analytic variables are responsible for its showing up so frequently but not invariably. As we noted earlier, studies beginning at or prior to onset of drinking (e.g., those beginning in early or mid-adolescence) cannot and do not find decreasing groups since there is little variability around a low or zero intercept. Additionally, as is clear in Feldman et al (2009), sometimes a soldier's bed may be found to be a best fitting model and still not chosen by researchers based on theoretical or logical reasons. The failure to adopt uniform rules for deciding upon the number of classes represents a further complexity in evaluating how common this phenomenon is in the published literature.

It is important to emphasize that the “cat's cradle” phenomenon appears across alternative measures of alcohol involvement (Jackson & Sher, 2005) and in studies where the intercept is set to some external event (such as post-partum patterns of drinking frequency; Oxford et al., 2003). Equally important, it does not appear to be limited to alcohol-related phenomena. That is, we can observe these patterns in non-alcohol related data including both other substance use (e.g., tobacco; Hu, Muthén, Schaffran, Griesler, & Kandel, 2008) and conduct problems (Odgers et al., 2007).

We also note that one major assumption in the majority of published trajectory-based approaches is that the intercept is the age of first observation and time is chronological age. This may not be the most useful way to think of trajectories of drinking if we believe that there is meaningful individual variation in the rate of escalation, persistence, and desistence since there are a large number of variables that determine initial age-of-onset of drinking (e.g., opportunity to drink) that may be irrelevant to course as it is typically viewed. Instead, it might be more useful to think of the intercept as a meaningful time zero as indicated by the initiation of drinking with chronological age representing a potential moderator of course (and has been done in studies of “telescoping”; Hussong, Bauer, & Chassin, 2008; Jackson, 2010; Sartor, Lynskey, Heath, Jacob, & True, 2007). That is, the currently employed approach confounds chronological/developmental age with stage of use (age of the “problem”). As discussed by Sher, Gotham, and Watson (2004), the correlates of use at a given age may be different than the correlates of stage of use and our currently employed methods often obscure this important difference.

More generally, researchers should consider alternative ways of thinking about the nature of the data being modeled (e.g., is the intercept time of first observation or time of first drink. To add further complexity, the seemingly straightforward notion of time of first drink can be operationalized in a variety of ways (e.g., first sip, first full drink, first regular use, first experience of heavy episodic drinking; Donovan, 2004). However, we believe that it is also important to consider methodological variables that can affect the nature and number of trajectories extracted. For example, it is known that a class structure can be an artifact of several skewed variables (see Bauer & Curran, 2003), and a relatively small number of skewed variables can distort any meaningful distinctions between classes (Steinley & Brusco, 2008), causing the estimated classes to recover instantiations of the observed skew – that is, analysis of repeated measurements of a skewed variable could result in extraction of too many classes. Furthermore, it is unclear how the binary nature of the data used in the present analyses may influence the different types of classes that can be extracted. Clearly, with two times of measurement and a binary variable, the solutions are logically and trivially constrained to a soldier's bed (present/present, present/absent, absent/present, and absent/absent) but this is far from the case as we increase the number of measurement occasions as we have shown here and the manifest number of patterns, in principle, could reach $2^{\#\text{ of ocassions}}$. Indeed, we find stronger evidence for the soldier's bed pattern with eight measurement occasions than with fewer occasions indicating that our findings are not simply preordained by logically constrained patterns. Furthermore, when employing these types of models, a general assumption is made that there is a linear component, and at times, a quadratic component (rarely do the data support modeling numerous groups with polynomial terms that exceed quadratic); however, it is entirely possible that these types of curves represent a bastardization of a highly nonlinear process that is not commonly modeled because they are often seen as more “complex” and more difficult to explain. As such, the linear (or quadratic) modeling approach may be causing a fragmentation of a set of nonlinear curves that leads to an incomplete interpretation of the results at best, and an oversimplication and misleading interpretation at worst.

The common finding of the soldier's bed suggests another analytic possibility; we might want to consider this variant of the cat's cradle a type of null model to test other trajectories against. That is, are there groups that emerge beyond those that are stably low, stably high, increasing or decreasing? If not, the utility of group-based trajectories can be seriously questioned. That is, the ubiquity of the cat's cradle indicates that it is the least interesting in terms of possible solutions for the reason just described. Thus, more interesting groups of trajectories will be the ones that deviate from the “logical occurrence”, or in effect, be something that deviates enough from the norm to be surprising.

As we have noted in our earlier work (Jackson & Sher, 2005; 2006; 2008), it may be better to use theory to define subgroups rather than basing groups on empirical findings from trajectory analyses. Such an approach is not without hazard, and one always risks overcapitalizing on chance or having too many “unclassified” subjects who do not fit into a theoretically derived group. Alternatively, statistically derived groups from mixture models

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can be used to supplement or validate theoretically derived trajectories (see Sher et al., 2004) to serve as a check that our theoretical notions are not too discrepant from our data. Although there may be great insight gained from purely exploratory, “brute force” empirical derivation of trajectory groups, our prior (Jackson & Sher, 2005; 2006; 2008) and current findings suggest that there is nothing inherent in these techniques that guarantees derived trajectories represent valid groups.

In a thoughtful discussion of conceptual issues surrounding the nature and interpretation of statistically derived trajectory groups, Nagin and Tremblay (2005) caution against reifying these trajectory groups despite the temptation many researchers have to do so. They also note that the number and nature of trajectory groups are not fixed properties of the individuals making up a sample. The abstract and approximate (and potentially arbitrary) nature of trajectory groups have been discussed by many others as well (e.g., Cudeck & Henley, 2003; Rindskopf, 2003; Sampson & Laub, 2005) along with the potential for artifactual findings (Bauer & Curran, 2003; but see Muthen, 2003). We view our current conceptual and empirical analyses as complementing those of others in that our findings strongly argue against reification of statistically derived groups and the conditional nature of groups based on critical method variables.

Before concluding, we raise the possibility that studies that cover a long time span may be underpowered to detect more than four classes due to insufficient *N*. However, in our review of the literature, we did not detect any systematic relation between sample size and number of classes extracted in studies with extended observation periods. Indeed, several studies with quite large sample sizes identify trajectories reflecting a cat's cradle pattern. For example, the study by Jackson, Sher, and Schulenberg (2009), which had a sample size of 32,087, identified the four prototypical classes, with the five-class solution failing to converge. Several other studies that exhibited the cat's cradle (as shown in Figure 1) had relatively large sample sizes (e.g., Jackson & Sher, 2008, N=3,058; Toumbourou et al., 2003, N=2,591; Tucker et al., 2005, N=6527), many of these with a large number of assessments (Jackson & Sher, 2008, 8 waves; Tucker et al., 2005, 6 waves). While some of these studies identified an additional trajectory (e.g., moderate use; fling use), one would expect more homogeneity in trajectories in a large sample simply because of more power to identify groups as N increases.

If one were to view derived trajectories as mere statistical abstractions to enhance data analysis, the issue we have addressed might be considered a relatively trivial one…akin to merely stratifying a data series according to some empirical or logical criterion. However, these groups are often assumed to have clinical or theoretical meaning. For example, Jacob et al. (2005) were surprised to recover a group of severe non-chronic alcoholics, a group with no counterpart in the literature and they comment “The results of the current effort provide evidence for the existence of four different drinking trajectories. Counterparts for three of these trajectories can be found in the larger alcoholism literature and, when related to current findings, provide a more complete understanding of their developmental nature. The fourth type has not been described in the extant literature, notwithstanding its seeming importance and prevalence (p. 752).” We, in fact, disagree with Jacob et al. in the sense that their “nonchronic severe class” can be viewed as a “decreasing class,” a finding entirely consistent with the cat's cradle literature. Similarly, in a study of youth age 7 to age 26, Odgers et al. (2007) identified a childhood-limited subtype of conduct disorder that was not predicted by theory. They note that “Based on the DSM-IV, the following 3 classes are expected: childhood onset, adolescence onset, and normative (low)” – yet in their study, “a childhood-limited subtype not specified by DSM-IV was revealed.” This group, although inconsistent with prior theory, is entirely consistent with the cat's cradle phenomenon.

Although much of this presentation has focused on illustrating inconsistencies in application of growth mixture modeling, the core issues highlight a thread that runs deeper through the mixture modeling, latent class, and cluster analysis literature. Specifically, as Steinley (2006, 2007) demonstrated, one of the chief concerns is the imposition of a cluster structure when it may not be appropriate. A recent study by Steinley and Brusco (in press) showed that this can happen when choosing the number of clusters (e.g., mixtures) is conflated with assessing the validity of a given group-based solution. Thus, just because a certain number of clusters may be indicated by a particular fit statistic (for example, BIC), it does not necessarily follow that the accompanying solution is replicable or generalizable (e.g., the cluster recovery can still be poor even if the BIC indicates the fit is good). Conversely, a replicable solution does not guarantee that the associated number of groups is the correct number. Taken with these prior results, the current study could potentially point to the over-reliance of practitioners on fit statistics for both choosing the number of clusters and assessing the quality of the fit. Future research should focus on disentangling these two processes where, even after a fit statistic indicates a particular number of clusters, the solution will be subjected to a validation process. We recognize that there may be situations where mixture-type approaches to studying growth are motivated by properties of the data distribution independent of substantive interest in subpopulations (Feldman et al., 2009) and the concerns highlighted in this manuscript do not directly address this type of issue. Moreover, our critique focuses on so-called “person-centered” approaches (e.g., longitudinal mixture analyses uses including longitudinal latent class models, longitudinal growth mixture models, longitudinal latent profile analyses). Individual differences in trajectories are also captured in variable-centered approaches including traditional latent gsrowth models and longitudinal hierarchical linear models. By their very nature, these models will involve less adjudication among competing models and thus, less hazard in choosing an incorrect model. Thus, whenever choosing a group-based, person-centered approach over these variable-centered approaches, a strong rationale should be provided.

The author of *Cat's Cradle*, Kurt Vonnegut (1963), distinguished between two types of interpersonal groups, the *karass* and the *granfalloon.* The karass is what we might consider to be a fundamentally valid group where individuals within the karass share a deep affiliation or linkage (in our case, sharing a fundamentally valid “groupness”) as opposed to a *granfalloon* which is a “fake karass” (bearing superficial resemblance to a real group but lacking valid groupness). In this context, we view statistically derived trajectory groups as posing a high risk for being granfalloons. The granfalloons can help us recognize different temporal patterns of variation in the course of problem behaviors (or disorders) over the life span and be useful statistical abstractions in some circumstances. However, if our goal is to find fundamental developmental karasses, we may be more likely misled than enlightened.

Acknowledgments

This paper is dedicated to the memory of Kurt Vonnegut (1922-2007). We would like to thank Dan Bauer who provided helpful comments on an earlier draft of this manuscript. Preparation of this paper was supported by National Institute on Alcohol Abuse and Alcoholism Grants K05AA017242 and R37AA007231 to Kenneth J. Sher, K01 AA13938 to Kristina Jackson, and K25AA017456 to Douglas Steinley.

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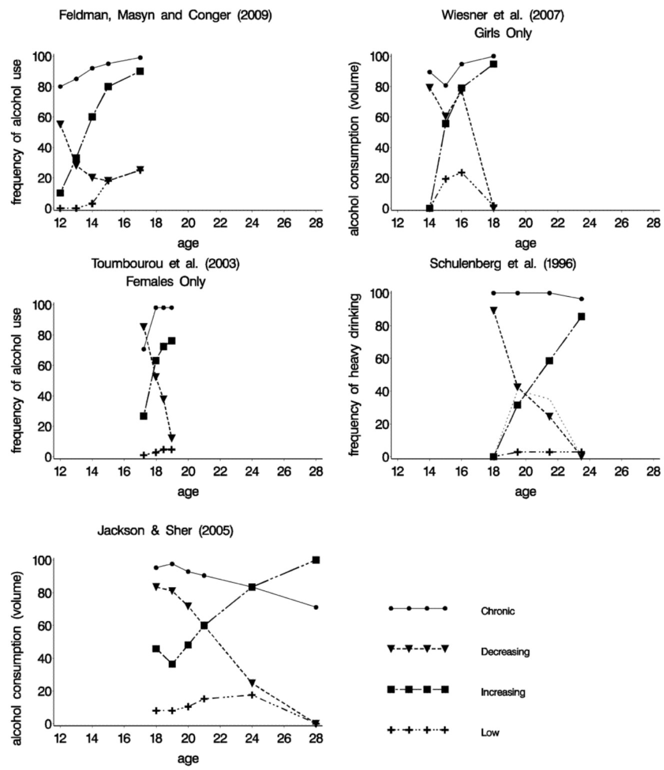

Figure 1.

Trajectories of various measures of alcohol involvement spanning ages 13-29 illustrating the “soldier's bed cat's cradle” phenomenon in five studies. All data have beeen scaled so that lowest reported value is a 0 and the highest reported value is 100 in each study.

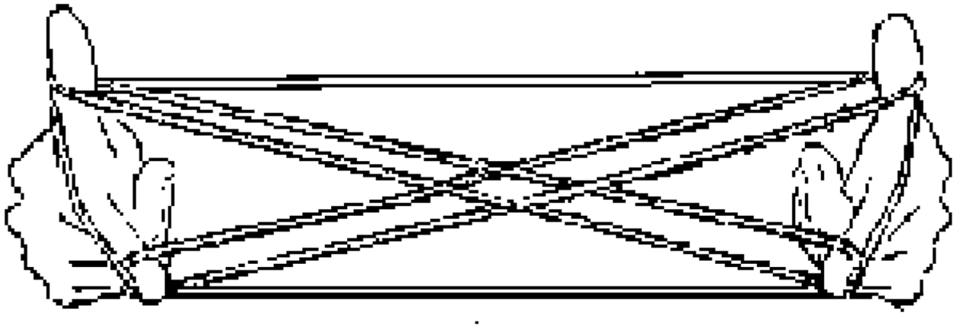

Figure 2.
Schematic for the soldier's bed variant of the cat's cradle (Lee, 2009). Reprinted with permission.

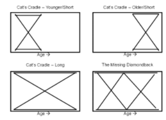

Figure 3.
Illustration of variations of prototypic “solider's bed” cat's cradle patterns as a function of chronicity and intercept (upper panel and lower left panel) and the missing “diamondback” pattern (lower right panel) (see text).

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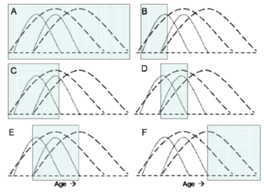

Figure 4.

Illustration of potential effects of observation windows, varying in duration and intercept, on trajectories (indicated by dotted and dashed lines) likely to be recovered assuming certain life course trajectories (see text). The y access for these panels represents prevalence or level of a relevant alcohol variable.

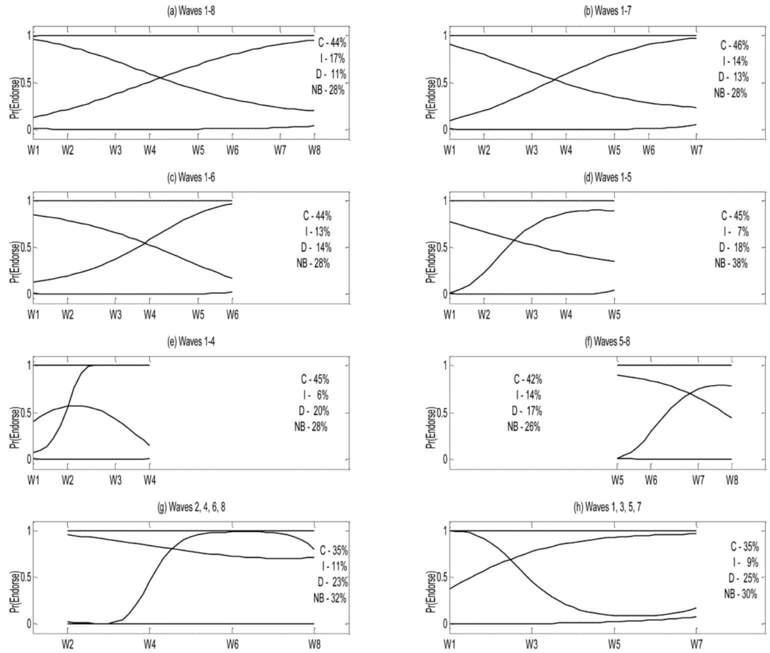

Figure 5.

Modeled derived growth trajectories for the eight models. The panels correspond to (A) Waves 1-8 (*N*=3,269); (B) Waves 1-7 (*N*=3,260); (C)Waves 1-6 (*N*=3,228); (D) Waves 1-5 (*N*=3,187); (E) Waves 1-4 (*N*=3,139); (F) Waves 5-8 (*N*=2,737); (G) Waves 1, 3, 5, and 7 (*N*=3,086); and (H) Waves 2, 4, 6, and 8 (*N*=3,041). *N*s for each trajectory group are model-derived class sizes.

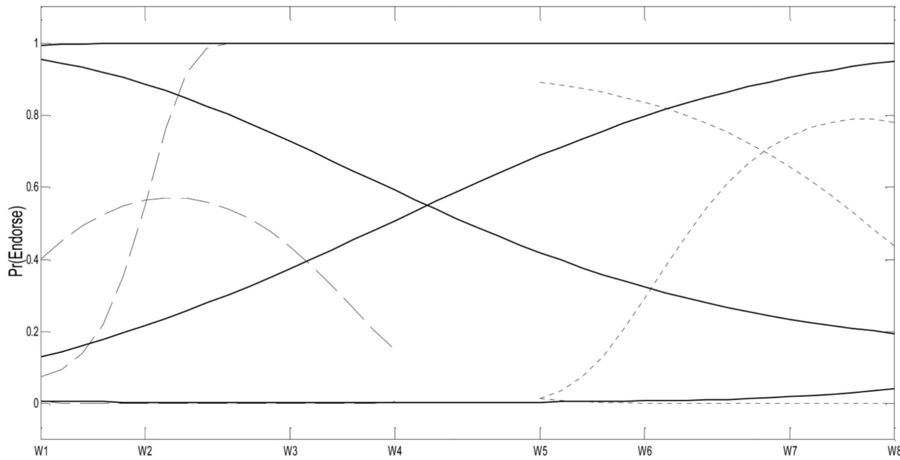

Figure 6.
Superimposition of the Wave 1-4 and Wave 5-8 model derived trajectories on the Wave 1-8 model derived trajectories illustrating the sharply different solutions obtained from each along with their logical incompatibility.

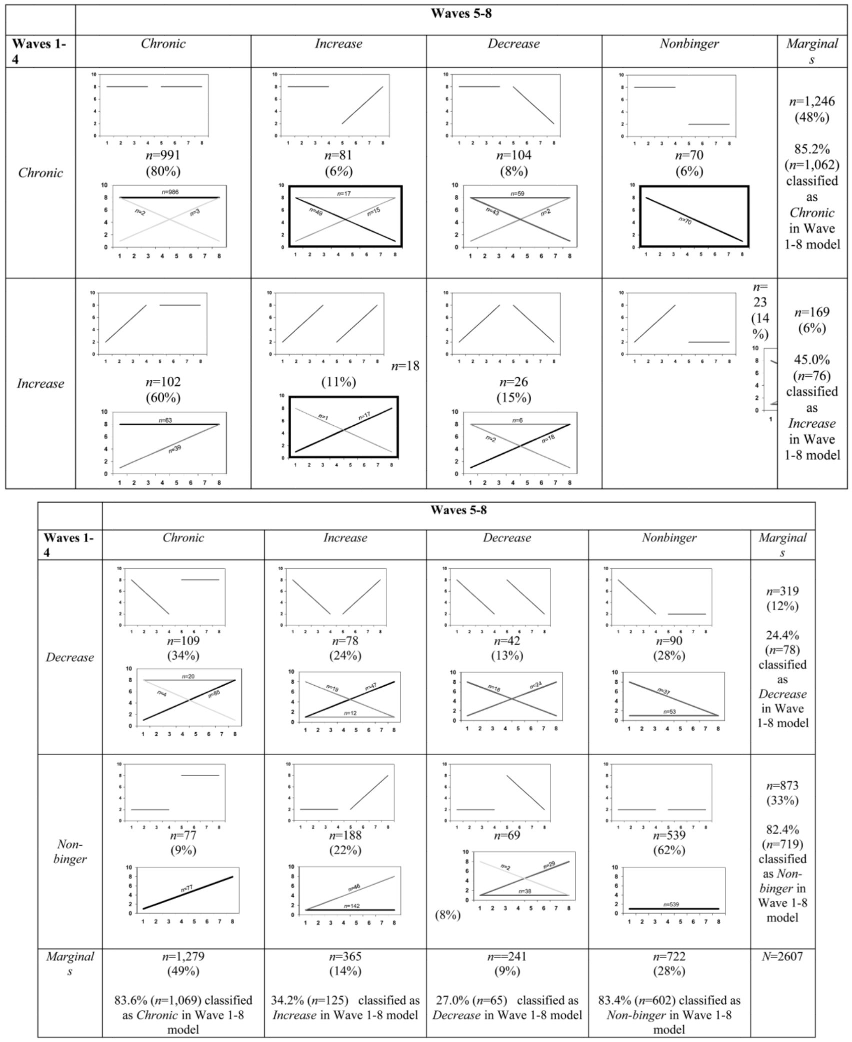

Figure 7.

Portrayal of how various combinations of “cat's cradle” patterns based on Waves 1-4 and on Waves 5-8 are represented in Waves 1-8 models. The figure represents all 16 combinations derived from the Wave 1-4 cat's cradle and the Wave 5-8 cat's cradle. Note that the percentages in each cell are row percentages; that is, the proportion of individuals in a given Wave 1-4 class who are in each of the four Wave 5-8 classes.

Table 1

Comparison of trajectories using Adjusted Rand Index (upper diagonal) and Cohen's Kappa (κ) (lower diagonal).

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Waves 1-8	--	*.88*	*.84*	*.76*	*.68*	*.59*	*.70*	*.70*
2. Waves 1-7	.90	--	*.90*	*.80*	*.70*	*.55*	*.70*	*.66*
3. Waves 1-6	.85	.91	--	*.83*	*.73*	*.52*	*.68*	*.66*
4. Waves 1-5	.76	.80	.84	--	*.76*	*.44*	*.68*	*.61*
5. Waves 1-4	.65	.69	.71	.80	--	*.34*	*.66*	*.54*
6. Waves 5-8	.58	.54	.48	.45	.40	--	*.49*	*.53*
7. Waves 1, 3, 5, 7	.75	.76	.74	.70	.67	.47	--	*.47*
8. Waves 2, 4, 6, 8	.73	.70	.71	.66	.59	.57	.54	--

Note. *N* ranges from 2,607 to 3,260. Cramer's V statistics are shown in italics above the diagonal; Cohen's kappa statistics are shown below the diagonal.

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Table 2

Fit indices and likelihood ratio tests for relative improvement in fit for heavy drinking.

Number of classes	Test of model fit	Waves 1-8	Waves 1-7	Waves 1-6	Waves 1-5	Waves 1-4	Waves 5-8	Waves 1, 3, 5, 7	Waves 2, 4, 6, 8
1 class	BIC	24860.98	22051.25	19042.89	15989.11	12958.33	11917.40	12453.24	12423.73
	VLMR LR	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2 classes	BIC	18219.14	16246.68	14136.47	12019.62	9956.95	9217.19	10232.91	10122.43
	VLMR LR	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$
3 classes	BIC	17635.30	15789.46	13843.63	11851.84 [a]	9894.71 [a]	9126.92	10207.38 [a]	10085.38 [a]
	VLMR LR	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .01$	$p < .001$
4 classes	BIC	17467.73	15668.63	13769.92	11847.19	9899.97	9128.19	10199.08 [a]	10086.21 [a]
	VLMR LR	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .01$	--	$p < .01$
5 classes	BIC	17428.22	15674.77	13784.06 [a]	11863.64	9931.66 [a]	9158.95 [b]	10229.84 [a]	10117.54 [a]
	VLMR LR	$p < .01$	$p < .01$	$p = .06$	$p < .05$	$p = .52$	$p = .35$	$p = .27$	$p < .001$
6 classes	BIC	17431.77	15686.86	13803.24 [b]	11890.34 [a]	9963.87 [b]		10261.98[b]	10149.62 [b]
	VLMR LR	$p < .05$	$p = .13$	$p =.14$	$p = .08$	--		--	--
7 classes	BIC	17439.39	15706.88	13825.14	11922.20 [b]				
	VLMR LR	$p = .05$	$p = .22$	$p = .25$	$p = 1.00$				

Note. N ranges from 2,737 to 3,269. VLMR LR = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test for k vs. k+1 Classes.

[a] Parameters fixed to avoid singularity in the information matrix.

[b] Solution for this likelihood ratio test would not converge or there was a non-positive definite first-order derivative product matrix.