

ORIGINAL ARTICLE

# Heat Maps: A Technique for Classifying and Analyzing Drinking Behavior

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Heat maps are presented here as an innovative technique for evaluating longitudinal drinking outcomes. The Life Transitions Study followed alcohol dependent individuals for 2.5 years during 2004–2009 in a Midwestern city ( $N = 364$ ). The TimeLine Follow-Back obtained drinking information. Heat map results were compared with those obtained using growth mixture modeling. Heat map classes differed significantly on baseline clinical and demographic indicators. Data were gathered with support from NIAAA R01AA014442.

**Keywords** heat maps, longitudinal drinking data, drinking outcomes, alcoholism, longitudinal research, data visualization, drinking patterns

## INTRODUCTION

Many alcoholics drink sporadically and unpredictably, even after treatment. This phenomenon presents a challenge to researchers who seek to define drinking outcomes in ways that are meaningful and optimally useful. Researchers have measured drinking at the end of treatment, drinking at follow-up, achievement of abstinence at various intervals, and reduced drinking. These approaches have merits but do not capture the pattern of drinking over time. Knowing more about longitudinal drinking patterns can reveal rich information and inform intervention efforts. This study introduces heat maps as a novel way of studying longitudinal drinking patterns. A heat map is a method of visualizing two-dimensional data where the hue or intensity of color varies according to a given value criterion. A basic heat map is a “color-shaded matrix display” (Wilkinson & Friendly, 2009, p. 181). In a clustered heat map, similar color patterns are grouped together to reveal larger structural properties of the data (Wilkinson & Friendly, 2009). While heat maps have been used exten-

sively in the natural and biological sciences, this study is the first to apply the use of heat maps to drinking data and to validate the method by comparing results with those obtained by growth mixture modeling, a longitudinal data analytic technique.

The purpose of this study is to present heat maps as a method for classifying drinking data. Questions to be answered include the following: (1) How does the heat map approach compare with growth mixture modeling, a commonly used approach for classifying drinking patterns? (2) Do heat maps produce classes that are meaningfully distinct as defined by baseline demographic and clinical variables?

## METHODS

Data for this secondary analysis are derived from a longitudinal survey whose original aims were to investigate the contribution of spiritual and religious change to reduced drinking. To assess a variety of alcoholics, the sample of 364 was recruited from treatment and non-treatment sources: a university-based outpatient treatment program ( $n = 157$ ), a Veterans Administration outpatient treatment program ( $n = 80$ ), a moderation-based program ( $n = 34$ ), and untreated individuals from the local community ( $n = 93$ ). As part of the study, extensive data on covariates of drinking outcomes were collected, including baseline clinical characteristics, Alcoholics Anonymous (AA), and treatment involvement over time. Baseline diagnoses of alcohol dependence were assessed using the Structured Clinical Interview for DSM-IV Axis I Disorders (SCID; First, Spitzer, Gibbon, & Williams, 1997). Of the many measures collected, we will only describe those relevant to this discussion of graphical and statistical analysis techniques to analyze drinking patterns over time. Respondents provided drinking data every 3 months for 2.5 years.

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## Measures

To determine baseline differences among the heat map groups, several variables were analyzed including recruitment site, demographics (age, years of education, income, race, gender, marital status, employment), and clinical variables (drinking frequency, drinking intensity, drinking consequences, desire for abstinence, AA involvement, presence of family members with alcohol problems, previous treatment experience, age at first symptoms, frequency and current impact of negative life events, and positive and negative social support).

Drinking data were gathered every 3 months via the TimeLine Follow-Back Interview (Sobell & Sobell, 1992; Sobell, Brown, Leo, & Sobell, 1996). This provided information on drinking frequency and intensity for the prior 3-month period. *Drinking frequency* was measured by the percent days respondent was abstinent and the number of days since the respondent's last drink. *Drinking intensity* was measured by the average drinks per drinking day and the percentage of heavy drinking days.

*Drinking consequences* were measured by the Short Index of Problems scale (SIP; Miller, Tonigan, & Longabaugh, 1995). Cronbach's alpha for this sample at baseline was .93.

*Baseline desire for abstinence* was measured by a single-item question, "Is being abstinent from alcohol something you want to do?"

*AA involvement* was measured by a modified version of the Alcoholics Anonymous Involvement scale (Tonigan, Connors, & Miller, 1996). Two items related to meeting attendance were excluded as these questions were asked independently in the parent study. The modified version contained six items related to involvement in AA activities. Cronbach's alpha for this sample was .81.

*Presence of a family member with an alcohol problem* was measured by the single-item question, "Has anyone in your family had problems with alcohol?"

*Previous alcohol treatment* was measured by the single-item question, "Have you ever been in treatment before for your alcohol problem?"

*Age of onset of alcohol dependence* was determined by a single item from the SCID instrument, "How old were you when you first had (interviewer here lists symptoms previously mentioned)?" (First et al., 1997).

*The number of negative life events* and the *degree of their current effect* on respondents were measured by the Life Events Questionnaire (Brugha & Cragg, 1990).

*Positive and negative social support* were measured by the "Receiving Social Support and Social Undermining" measure (Vinokur & Caplan, 1987; Vinokur, Schul, & Caplan, 1987). Cronbach's alpha for this sample was .93 for positive social support and .88 for negative social support.

## Creation of Heat Map

Heat map categories were generated using mean drinks per drinking day at each 3-month time period and the conditional formatting feature of Microsoft Excel (Windows Office 2007). Drinks per drinking day were entered into the spreadsheet, with each row representing one partici-

pant and his or her mean drinks per drinking day for each consecutive 3-month period from baseline to 30-month (2.5 years) follow-up. Each cell in the spreadsheet represented 3 months of drinking. Next, conditional formatting was used to color code each cell. Coded dark grey, "heavy" drinking was defined as a mean of more than four drinks per drinking day for women and more than five for men. Coded medium grey, "moderate" drinking was defined as more than zero but less than four drinks per drinking day for women and more than zero but less than five drinks per drinking day for men. Coded light grey, "abstinence" was defined as zero drinks per drinking day. The white cells represented missing data. Men's and women's heavy drinking in this study were interpreted differentially according to the definition of binge drinking established by the National Institute on Alcohol Abuse and Alcoholism (NIAAA, 2004).

Once all cells were coded, each case was visually inspected and sorted according to drinking pattern. This heat map procedure was in effect a form of graphical cluster analysis – the groupings were inspired by the data based on conceptual and empirical fit and there was no formal goodness of fit test.

## Heat Map and Missing Data

Cases with final follow-up data were able to be classified into a heat map drinking pattern even if there were missing data between baseline and the final follow-up. However, a significant number of individuals ( $n = 79$ ) could not be classified into a heat map drinking category because of missing end-point data caused by the respondent dropping out of the study ( $n = 28$ ), failure to respond to outreach ( $n = 37$ ), or death ( $n = 14$ ). Therefore, out of the original 364 respondents, 285 cases were included in the heat map analysis.

## Growth Mixture Modeling

Mplus version 6.2 was used for growth mixture modeling. Upon first examination of mean drinks per drinking day over time, a pattern prevalent in the collection of drinking data in alcoholic samples was observed; that is, the initial data point was significantly higher than the trajectory of all subsequent time points. Because the first time point did not reflect the rest of the trajectory, we chose to eliminate this time point from the growth mixture model. The models, therefore, start with the second time point.

We first estimated a latent growth model to find the order of the polynomial that would provide a good fit to the shape of the average trajectory. A linear model had a decent fit, with Comparative Fit Index = .90 and Root Mean Square Error of Approximation = .093. A quadratic model generated an error until the variance of the quadratic term was set to zero. At that point, the model converged and the model fit was Comparative Fit Index = .90 and Root Mean Square Error of Approximation = .095. A delta-chi-square test showed that there was not a significantly better fit for this quadratic than the linear model ( $\Delta\chi^2(1) = -.43, p > .3$ ). Because we suspected that there were underlying distinct populations

that would be differentiated by their trajectories of drinking, we used growth mixture modeling to tease apart these populations. First, we modeled two linear classes. The Lo–Mendell–Rubin-adjusted likelihood ratio test did not show evidence that two linear classes provided better fit than one linear class. Second, we attempted to model a solution that was linear for one class and a quadratic solution for another class. This model produced errors (negative variances of growth parameters). Therefore, we chose to use Latent Class Growth Analysis which is a form of growth mixture modeling in which the variance of parameters within each class is set to zero.

### Growth Mixture Modeling and Missing Data

Mplus provided analysis of all of the data in the sample, with Full Information Maximum Likelihood analysis. The lowest value of the covariance coverage (a measure of the amount of missingness in the data) was 0.556. This falls well within the guidelines that each value of the covariance coverage matrix be greater than 0.5 (Schafer, 1997). Ten cases with only baseline data were eliminated; therefore, 354 cases were included in the growth mixture modeling analysis.

### Analysis Plan

The heat map classes and the growth mixture modeling classes were generated and visually inspected. The four heat map drinking pattern categories were compared on baseline demographic and clinical variables using chi square tests or one-way analyses of variance (ANOVAs). Crosstabs that revealed less than five observed values per cell were analyzed using the Fisher's exact test. For the race variable, categories were collapsed into "white" and "other" to produce an adequate number of cases per cell. To determine which groups were statistically different from other groups, adjusted standardized residuals were examined in the crosstab analyses and Tukey post hoc tests were examined in the one-way ANOVA. Groups with adjusted standardized residuals of  $\pm 2.5$  were identified to have statistically significant differences from other groups in the analysis. Adjusted standardized residuals of this magnitude are indicated in Table 1.

## RESULTS

### Heat Map Solution

Four general patterns emerged: "heavy," "stop-and-start," "moderate," and "abstinent." Visual inspection of the data suggested the following inclusion and exclusion criteria for each group. "Abstinence" ( $n = 96$ ) is the pattern of having achieved a minimum of 1-year abstinence at the 30-month final time point. "Stop-and-start" ( $n = 53$ ) is a pattern of drinking interrupted by either one 9-month period of abstinence or multiple periods of abstinence with one period of at least 6-month duration over the 2.5–3 years of the survey. "Moderate" drinking ( $n = 58$ ) featured a majority of cells coded moderate with a maximum of one cell of heavy drinking, or two cells of heavy drinking if the overall pattern represented a deceleration in drink-

ing. "Heavy" drinking ( $n = 78$ ) patterns had two or more cells of heavy drinking unless the individual fit criteria for stop-and-start, moderation, or abstinent drinking as defined above. Figure 1 features a heat map of six cases from each group to illustrate the visual patterns produced for each drinking pattern. Figure 2 displays the mean drinks per drinking day over time for each of the drinking patterns rendered by the heat map.

### Growth Mixture Model Solution

Using Latent Class Growth Analysis, we tested models with one linear class and one to three quadratic classes. In each case, the Lo–Mendell–Rubin-adjusted likelihood ratio test did not provide support for a better model fit of a higher number of classes than a lower number of classes ( $p > .14$ , for each of the models). However, the visual inspection of these models showed good differentiation between classes and each of the classes had a substantial number of members. Therefore, for substantive reasons and to compare with the heat map results, we chose the model with four classes, three quadratic and one linear. Figure 3 shows the four-class solution, with the estimated means and sample means at each time point. We named these classes "very heavy," "heavy increasing," "moderate decreasing," and "low." The most problematic class, "very heavy," was also the smallest. This class had 13 members, 3.7% of the sample, and had a high and only slightly decreasing trajectory of drinks per drinking day. The second 2 highest trajectory classes ("heavy increasing" and "moderate decreasing") comprised 10.5% ( $n = 37$ ) and 20.3% ( $n = 72$ ) of the sample, respectively. These classes each started at about six drinks per drinking day, but one of the classes had an increasing trajectory over the course of the study and the other had a decreasing trajectory. The "low" drinking class contained 65.5% ( $n = 232$ ) of the sample and showed a low and decreasing number of average drinks per drinking day over the 2.5 years.

### Comparison of Heat Map and Growth Mixture Modeling Approaches

A side-by-side comparison of Figures 2 and 3 provides a visual representation of the results of the two approaches. The heat map and the growth mixture modeling approaches each yielded four groups. The heat map approach was able to designate an abstinent and a stop-and-start group. Growth mixture modeling was able to classify cases with missing end-point data and thus included more cases (354 cases vs. 285 cases with heat maps). Neither classification system was able to classify 10 cases that contained baseline data only. Growth mixture modeling was able to display overall trends in drinking of each class, such as increasing or decreasing behavior. While the heat map approach identified heavy drinking, the growth mixture modeling approach stratified different intensities of heavy drinking. The heat map approach included baseline drinking, while the growth mixture modeling approach eliminated baseline drinking before analysis.

TABLE 1. Descriptive information for baseline variables by drinking pattern in the Life Transitions Study means (standard deviations) or percentages (adjusted standardized residuals if  $\pm 2.5$ )

Variable (% sample)	Heavy ( <i>n</i> = 78, 27.4%)	Stop-and-start ( <i>n</i> = 53, 18.6%)	Moderate ( <i>n</i> = 58, 20.4%)	Abstinent ( <i>n</i> = 96, 33.7%)	<i>p</i>
<b>Demographics</b>					
Marital status					.000
Never married (28.1%)	44.9% (3.9)	28.3%	17.2%	20.8%	
Married/living with significant other (40.7%)	29.5%	30.2%	67.2% (4.6)	39.6%	
Separated, divorced, or widowed (31.2%)	25.6%	41.5%	15.5% (-2.9)	39.6%	
White race* (81.1%)	71.8% (-2.4)	73.6%	91.4%	86.5%	.007
Age	40.6 <sup>a</sup> (14.1)	45.6 (12.9)	44.7 (11.6)	48.1 <sup>a</sup> (11.4)	.002
Years of education	14.1 <sup>a</sup> (2.0)	13.5 <sup>b</sup> (2.3)	16.3 <sup>a,b,c</sup> (2.8)	14.5 <sup>c</sup> (2.1)	.000
Household income					.004
< \$15,000 (27.1%)	34.6%	34.0%	8.8% (-3.5)	28.1%	
\$15,001-\$85,000 (49.6%)	47.4%	47.2%	50.9%	52.1%	
\$85,001+ (23.2%)	17.9%	18.9%	40.4% (3.4)	19.8%	
Employed (57.5%)	56.4%	49.1%	77.6% (3.5)	51.0%	.005
Male (65.3%)	60.3%	79.2%	56.9%	66.7%	n.s.
<b>Clinical baseline data</b>					
Percent days abstinent	46.3 <sup>b,d</sup> (31.4)	65.5 <sup>c,d</sup> (26.0)	48.7 <sup>a,c</sup> (31.1)	63.6 <sup>a,b</sup> (31.7)	.000
Percent heavy drinking days	44.0 <sup>b,c,d</sup> (31.1)	27.5 <sup>d</sup> (23.9)	17.8 <sup>a,c</sup> (22.4)	31.4 <sup>a,b</sup> (30.9)	.000
Drinks per drinking day	9.5 <sup>a</sup> (5.9)	11.6 <sup>b</sup> (8.7)	4.3 <sup>a,b,c</sup> (3.7)	9.7 <sup>c</sup> (8.7)	.000
Days since last drink	14.8 <sup>b,d</sup> (22.8)	31.9 <sup>c,d</sup> (26.0)	12.6 <sup>a,c</sup> (23.2)	38.6 <sup>a,b</sup> (30.2)	.000
Age at first symptoms	28.0 (11.7)	27.9 (12.4)	30.0 (13.2)	30.0 (12.6)	n.s.
Negative consequences (SIP)	19.4 <sup>a</sup> (11.7)	24.3 <sup>b</sup> (11.7)	13.5 <sup>a,b,c</sup> (9.2)	22.8 <sup>c</sup> (10.7)	.000
Alcoholics Anonymous involvement (AAI)	1.6 <sup>b,d</sup> (1.8)	2.7 <sup>c,d</sup> (2.1)	0.6 <sup>a,b,c</sup> (.8)	2.2 <sup>a</sup> (2.1)	.000
Negative life events (LEQ)	2.2 (1.8)	2.5 <sup>a</sup> (1.9)	1.5 <sup>a,b</sup> (1.7)	2.3 <sup>b</sup> (1.7)	.018
Negative life events still affecting you (LEQ)	2.1 (1.6)	2.3 (1.5)	2.1 (1.4)	2.1 (1.4)	n.s.
Positive social support	3.7 (.9)	3.4 <sup>b</sup> (.7)	3.8 <sup>a,b</sup> (.7)	3.4 <sup>a</sup> (.8)	.007
Negative social support	1.8 <sup>a,b</sup> (.7)	2.2 <sup>a</sup> (.7)	1.9 (.6)	2.0 <sup>b</sup> (.7)	.005
Want to be abstinent? Yes (69.8%)	61.5%	86.8% (3.0)	36.2% (-6.2)	87.5% (4.6)	.000
Alcohol Problem in Family? Yes (86.3%)	83.3%	92.5%	87.9%	85.3%	n.s.
Previous alcohol treatment? Yes (51.2%)	51.3%	73.6% (3.3)	19.0% (-5.6)	58.3%	.000

Note: *N* = 285 except for negative life events (*n* = 283) and negative life events still affecting you (*n* = 223), SIP = Short Index of Problems scale, AAI = Alcoholics Anonymous Involvement Scale, LEQ = Life Events Questionnaire.

\*Compared with people of color in this sample: African Americans (*n* = 29), Hispanics (*n* = 5), Native Americans (*n* = 4), Asians (*n* = 2), multiracial individuals (*n* = 11), and others (*n* = 3).

<sup>a, b, c, d</sup> Pairings in superscript indicate statistically significant differences between drinking pattern groups.

### Differences Among the Heat Map Groups

Analyses revealed statistically significant differences among the four heat map groups. See Table 1 for a report of the results.

First, differences by recruitment site were observed. Heavy drinkers were more likely to come from the untreated community sample and less likely to come from the university outpatient treatment program. Stop-and-start drinkers were more likely to come from the Veterans Administration treatment program and less likely to come from the moderation program. Moderate drinkers were more likely to come from the community or the moderation program and less likely to come from either outpatient treatment program. Those who achieved a year of abstinence were more likely to have come from the university treatment program and less likely to have come from the untreated community sample.

### DEMOGRAPHICS

Heavy drinkers were more likely to have never married. Moderate drinkers were more likely to be married or living with their significant other and less likely to be separated, divorced, or widowed. Moderate drinkers were also less likely than the other groups to be earning less than \$15,000 per year and more likely to be earning more than \$85,000 per year. Moderate drinkers were also more likely to be employed and had more years of education than the other groups. Each of these differences was statistically significant. The abstinent group was oldest in age of all groups with significant differences compared with heavy drinkers (48.1 vs. 40.6 years old, respectively). In this sample, Whites were less likely to be heavy drinkers, and people of color were more likely to be heavy drinkers. There were no significant differences between the four groups in terms of gender.

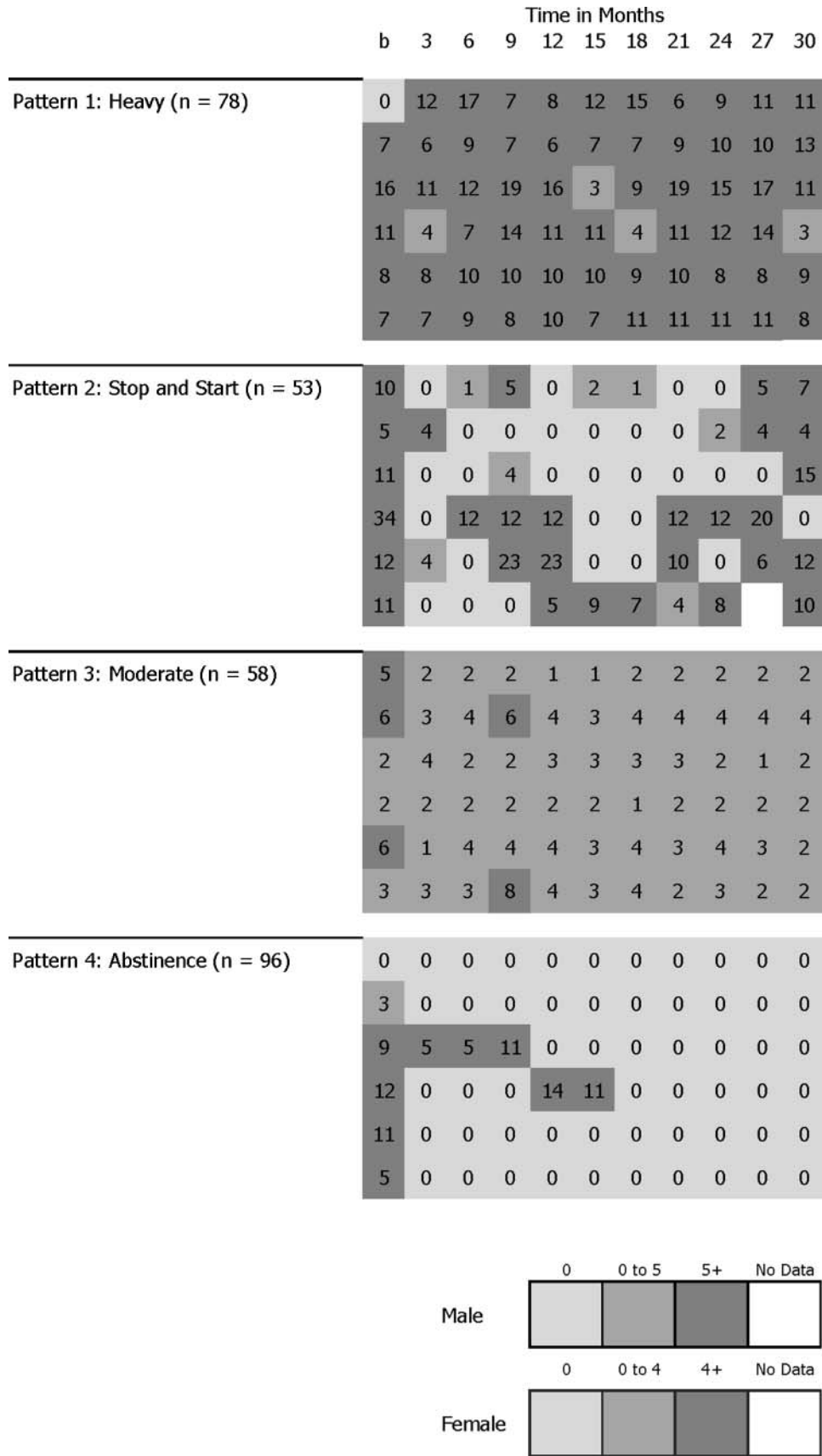


FIGURE 1. Heat map of six examples from each drinking pattern. Numbers within the figure represent mean drinks per drinking day in each 3-month period (rounded).

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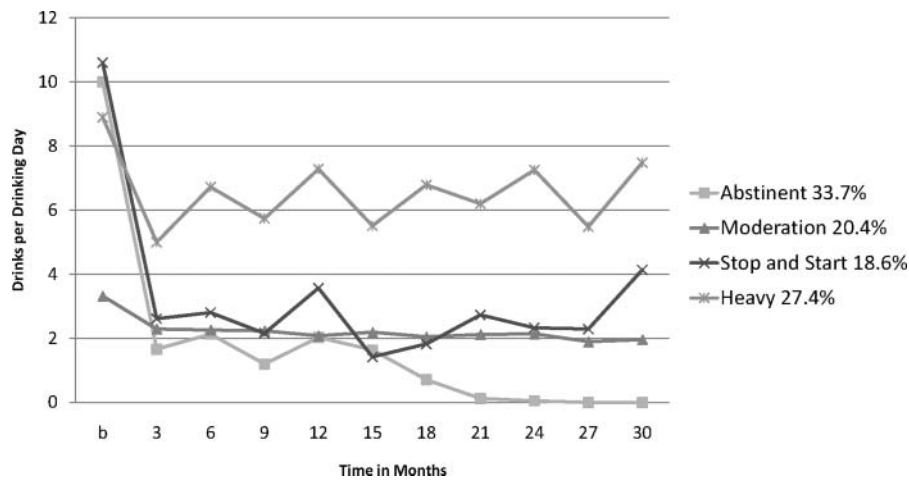


FIGURE 2. Drinking intensity by heat map category ( $N = 285$ ).

### BASELINE CLINICAL VARIABLES

At baseline, the moderate group had the lowest drinks per drinking day, lowest number of days since last drink, and fewest negative consequences of drinking compared with the other groups. They had the lowest levels of AA involvement, lowest desire for abstinence, and lowest rates of previous treatment for alcohol problems. The heavy drinkers had lowest percent days abstinent, highest percent heavy drinking days and second lowest desire for abstinence after the moderate drinkers.

The majority of all groups (ranging from 83.3% to 92.5%) stated that they have a family member with alcohol problems; there was no statistically significant difference among groups on this issue. The moderate drinkers reported lowest levels of negative life events and highest levels of positive social support. The stop-and-start group had the highest levels of negative social support. The heavy drinkers reported lowest levels of negative social support.

### DISCUSSION

The main findings of this study were the following: (1) Heat maps made a unique contribution above and beyond growth mixture modeling by allowing theory to guide classification resulting in a fully abstinent and a stop-and-start category of drinkers. It is an approach that can be produced without advanced statistical procedures and can be created with widely available software (Microsoft Excel). However, cases are categorized one at a time, by hand, which would be possible only for smaller data sets and there is an absence of a formal statistical test to determine goodness of fit of the heat map groupings. (2) Growth mixture modeling made a unique contribution above and beyond heat maps in its ability to include missing data. It created classifications that were statistically justified and provided statistical tests to choose the number of classes. Its primary drawback is that it could not efficiently model multiple increases and decreases in outcome as represented in the heat map “stop-and-start” grouping. (3) Heat

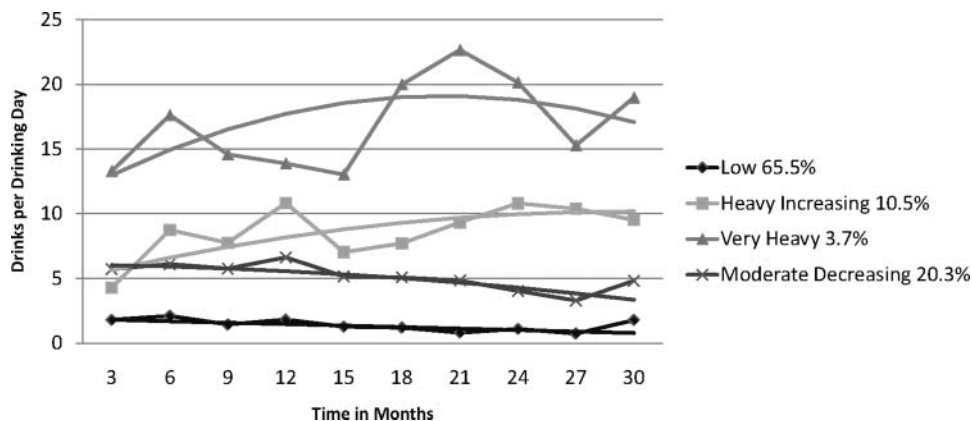


FIGURE 3. Drinking intensity by growth mixture modeling class actual and estimated means ( $N = 354$ ).

map classifications were statistically different from one another on baseline demographic and clinical indicators. Of specific note is the social and economic privilege of the “moderate” drinkers and the finding that people of color were more likely to be in the “heavy” drinking classification.

Meaningful differences among heat map groups at baseline suggest implications for future research and practice. Stop-and-start drinkers may represent a high-risk group and yet may include individuals on the verge of long-term recovery. Our analysis revealed that this group had a mix of significant strengths and weaknesses compared with other groups. They had significantly more previous treatment for an alcohol problem, higher AA involvement, higher percent days abstinent, and higher desire to be abstinent, but also had more negative consequences of drinking, more negative life events in general, and higher negative social support. It may be that high negative life events and negative social support are obstacles to the achievement of long-term recovery even when abstinence is desired. Further study of this subgroup, now that it has been identified, could yield improved intervention strategies for those who desire sobriety, gain it for significant periods, but continually relapse.

Individuals diagnosed with alcohol dependence who demonstrate moderate drinking are of interest to alcohol researchers. This study revealed them to be significantly different along a host of key socioeconomic and clinical variables. The moderate drinking group was disproportionately privileged. They were more likely to make more than \$85,000 a year and more likely to be employed and married. They had higher levels of positive social support. They were less likely to want to be abstinent, had fewer previous treatment episodes, and had less experience with AA. They had also suffered fewer negative life events generally and fewer negative consequences of drinking. Perhaps negative life events and harmful drinking consequences are necessary to motivate an individual toward 100% abstinence. The social class difference is particularly important to note. More research on the protective factors of socioeconomic privilege is warranted. Increased understanding can help illuminate the interaction of alcohol dependence, drinking behavior, and social class.

Differences at baseline reveal possible predictors of long-term abstinence. The abstinent group respondents were older in age, had higher percent days abstinent at baseline, more days since last drink, more of them wanted to be abstinent, more had prior AA involvement, and more had experienced negative effects from drinking. This information can be used clinically to identify clients who may be more successful at achieving long-term abstinence, which can inform treatment planning.

The heavy drinkers revealed themselves even at baseline to be a high-risk group. They were more likely to have never married, more likely not to want abstinence, and had the highest percentages of days of heavy drinking. Heavy

drinkers were also more likely to be individuals of color, suggesting racial health disparities in this sample. Again, further study can yield rich information about chronic alcoholism, as it is stratified by levels of social class and disadvantage.

It is important to note that the heat map groups were equivalent at baseline on several variables. The majority of individuals in all four groups indicated that they had a family member with an alcohol problem. Other similarities across the groups are the age when individuals manifested their first problems with alcohol and gender composition. These characteristics are shared among alcoholics despite the course of the disease. These variables are not predictive of later drinking patterns.

A heat map of drinking patterns in a longitudinal study is valuable as it provides a stronger sense than many other techniques of both individual and group outcomes. Besides obtaining a snapshot of each person’s drinking career, it also serves the research team as a valuable at-a-glance guide to clusters of outcomes across a sample. It makes easier the task of identifying specific cases with drinking trajectories that may be of interest.

## LIMITATIONS

When interpreting the findings of this study, an important consideration is our definition of moderate drinking. While we used NIAAA’s definition for binge drinking as a guideline in establishing that four or more drinks per day for women and five or more drinks per day for men would constitute the line between moderate and heavy drinking, it is important to note that other established guidelines are more stringent. The Centers for Disease Control and Prevention (CDC) defines heavy drinking as an average of more than two drinks per drinking day for men and more than 1 drink per drinking day for women (CDC, 2010). One compelling idea for future research would be to further stratify the drinking categories used in this study to differentiate levels of moderate drinking according to CDC’s definition and, as was demonstrated in the growth mixture modeling groupings, to differentiate heavy drinkers into heavy (5+ drinks per drinking day) and very heavy (15+ drinks per drinking day) intensities of drinking consumption. The heat map approach easily can be adapted to render these finer grained group differences.

In addition, the averaging of drinks per drinking day over 3-month muted spikes in drinking indicative of bingeing and other more problematic drinking behaviors. It is important to note that we have no information on the time frame within which drinks were consumed. Four or five drinks within a 2-hour period represents binge drinking according to NIAAA’s definition (NIAAA, 2004). This is particularly important when interpreting the findings for the individuals in the current study’s moderation group. Further research should investigate daily or weekly drinking for these individuals (see Stout, 2000), should consider the CDC definition for moderate drinking, and the time frame in which drinks were consumed.

Another limitation relates to the method used to classify drinkers. While the group criteria were inspired by the data itself, cut offs between groups and judgments about borderline cases were made with a degree of subjectivity. Finally, as mentioned, hand classification, as was possible in this study of 364 alcoholics, would be possible only in smaller datasets. Much larger datasets would require computerized methods.

In summary, this analysis highlights the utility of using heat maps to categorize participants in alcoholism research and compares this technique with growth mixture modeling. Growth mixture modeling included more cases with missing data and created classes that were statistically justified; however, it could not model drinking patterns characterized by multiple increases and decreases. Using the heat map approach, cases were classified individually by visual inspection, and it was not possible to render a statistical goodness of fit test. However, heat maps allowed theory to guide classification, were produced without advanced statistical techniques using Microsoft Excel, and provided rich information hidden by growth mixture modeling, for example, the discovery of a class of drinkers who have a stop-and-start pattern. The identification of this subgroup enables further study of individuals with these patterns. The classes produced by the heat map differed on baseline demographic and clinical indicators.

This study is the first that we are aware of to apply the data visualization technique of heat maps to the interpretation of longitudinal drinking data. New research highlights the advantages of using drinking classes as outcomes in alcoholism research (Gueorguieva et al., 2010). Despite limitations, this study demonstrates the utility of heat maps as an innovative method for classifying drinkers' outcomes and for visualizing and understanding drinking data.

### Declaration of Interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the article.

### RÉSUMÉ

#### Cartes Thermiques: Une Technique de Classification et d'Analyse des Comportements face à l'Alcool

Des cartes thermiques sont présentées ici en tant que technique innovante pour l'évaluation longitudinale des résultats dans le domaine de la consommation de boissons alcoolisées. L'étude "Transition de vie" a suivi pendant 2.5 ans des individus dépendants à l'alcool au cours de la période 2004–2009 dans une ville du Midwest ( $N = 364$ ). Des entrevues de suivi linéaire (TimeLine Follow-Back) ont ensuite permis l'obtention d'informations sur leur consommation d'alcool. Les résultats, présentés sous forme de cartes thermiques, ont été comparés à ceux

obtenus en utilisant des modèles mixtes de croissance. Les classes des cartes thermiques diffèrent significativement en termes de niveaux de référence cliniques et démographiques. Les données ont été recueillies avec le soutien de NIAAA R01AA014442.

### RESUMEN

#### Mapas de calor: Una técnica para clasificar y analizar longitudinalmente el consumo de alcohol

Mapas de calor son presentados aquí como una técnica innovadora para la evaluación de longitudinal del consumo de alcohol. El Estudio sobre Transiciones en la Vida siguió personas con dependencia de alcohol por 2.5 años durante 2004–2009 en una ciudad del Medio Oeste del EEUU ( $N = 364$ ). La información sobre hábitos de consumo se obtuvo usando el método de registro en calendario de eventos. Los resultados de los mapas de calor fueron comparados con los resultados obtenidos usando modelos mixtos de análisis de crecimiento. Las clases de los mapas de calor diferían significativamente en los primeros indicadores clínicos del pre test y en características demográficas de los participantes. Los datos fueron conseguidas con el financiamiento de NIAAA R01AA014442.

### THE AUTHORS



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**Dr. Elizabeth A. R. Robinson** is a Research Assistant Professor, funded by the NIAAA, Metanexus Institute and Fetzer Institute. Her recent work has focused on recovery from alcoholism and the role of spiritual and religious change. She is also interested in the potential usefulness of mindfulness-based strategies as an adjunct to treatment and/or AA involvement. Dr. Robinson's

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**Dr. Jennifer M. Jester** joined the University of Michigan Addiction Research Center in 2000. Her Ph.D. is in biomedical engineering from the Johns Hopkins University. Her research focuses on longitudinal studies of children and adults in alcoholic families. She uses multiple statistical techniques such as growth mixture modeling to look at the effects of behavioral traits and

environmental conditions on children's outcomes. She is also interested in interventions in these high-risk families to improve parenting and ameliorate ill effects for the children.



**Dr. Brian E. Perron** joined the faculty at the University of Michigan, School of Social Work after completing his Ph.D. at Washington University in 2007. Previously, he worked as a clinical social worker in community mental health, providing services to persons with serious mental illnesses and substance use disorders. His research focuses on issues related to the quality of

care for persons with mental illnesses and substance use disorders. He is involved in a variety of research activities, including analysis of nationally representative data and clinic-based surveys and collaborating on field-based interventions. Dr. Perron is also interested in innovative research methodologies and provides statistical consultation for a number of projects.

## GLOSSARY

**Heat Map:** A heat map is a method of visualizing two-dimensional data where the hue or intensity of color varies according to a given value criterion.

**Clustered Heat Map:** In a clustered heat map, similar color patterns are grouped together to reveal larger structural properties of the data.

**Growth Mixture Modeling (GMM):** Growth mixture modeling is a procedure that examines cases in a given data set and identifies subpopulations that are referred to as "classes." Classes are made up of cases that are similar to one another in either longitudinal change or differences in patterns of change.

**Latent Class Growth Analysis (LCGA):** A form of growth mixture modeling in which the variance of parameters within each class is set to zero. This approach is used

when the relationship between the independent and dependent variables differs in both strength and direction.

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