Alcohol Use Trajectories Among Non–Treatment-Seeking Heavy Drinkers

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ABSTRACT. Objective: Heavy drinking, often defined as more than five drinks per occasion, is a major public health problem worldwide, yet most individuals who drink heavily never receive treatment. Focusing on those who receive treatment, numerous studies have found that alcohol use following treatment is discontinuous, with periods of abstinence alternating with periods of heavy drinking. In contrast, little is known about changes in alcohol use among the majority of individuals who engage in heavy drinking and never receive treatment. The goal of this study was to examine changes in alcohol consumption (proportion of heavy drinking days) in a sample of non–treatment-seeking heavy drinkers ($n = 151$). **Method:** The current study focused on three quantitative models—latent growth curve, latent growth mixture, and latent Markov models—to examine changes in the frequency of heavy drinking days

(i.e., $\geq 5/4$ drinks per day for men/women) among a sample of heavy drinkers who did not receive any form of treatment or self-help over a 2-year period. **Results:** Participants significantly reduced their frequency of heavy drinking over a 2-year period, and changes in drinking did not show the discontinuity in trajectories often observed in treatment samples. Alcohol use disorder diagnosis predicted higher initial levels of frequent heavy drinking but did not predict changes in the frequency of heavy drinking over time. **Conclusions:** Most individuals, with or without an alcohol use disorder, reported significant reductions in heavy drinking frequency over time. These results have important implications for a public health approach to the problem of heavy drinking. (*J. Stud. Alcohol Drugs*, 75, 415–422, 2014)

HARMFUL ALCOHOL USE is a global public health problem resulting in 2.5 million deaths worldwide each year (World Health Organization [WHO], 2011). Prevalence of alcohol use disorders (AUDs) worldwide ranged from 0% to 16% in 2004 with rates of heavy drinking (defined as more than five drinks per occasion) greater than 20% in many countries (WHO, 2004). Of importance is that few of those who engage in heavy alcohol use will ever receive treatment. In the United States, it has been estimated that only 24.1% of individuals with lifetime AUD have ever received treatment (Hasin et al., 2007), and there is a substantial unmet need for treatment in most countries (WHO, 2011).

Despite the large number of individuals who engage in heavy alcohol use, there are few prospective studies of non–treatment-seeking heavy drinkers. Such research is crucially important to gain a better understanding of the scope of the problem as well as possible opportunities for prevention and intervention. Those studies that have recruited non–treatment-seeking heavy drinkers (Dearing et al., 2013) as well as population samples that include heavy drinkers (e.g.,

Dawson et al., 2005; de Bruijn et al., 2006) have often found that heavy drinking tends to decrease over time, even in the absence of treatment. In many cases heavy drinkers can change to moderate, nonproblem (nonheavy) drinking that is sustained (Klingemann et al., 2010; Sobell et al., 2002; Tucker and Simpson, 2011; van Amsterdam and van den Brink, 2013).

Despite evidence that many individuals who engage in heavy drinking are able to reduce their drinking without treatment, very little is known about patterns of drinking changes among those who reduce heavy drinking in the absence of treatment. Prospective studies of drinking trajectories among non–treatment-seeking heavy drinkers provide a crucial reference group for many brief intervention studies, which are often conducted with non–treatment-seeking heavy drinkers (Fleming et al., 1997, 2010; Hansen et al., 2012). Recently a meta-regression of control group outcomes in brief intervention studies indicated that significant reductions in drinking were often observed among control group participants; however, for many studies, the change in drinking among control group participants was unclear or control group data were not collected at follow-up (Jenkins et al., 2009). Jenkins and colleagues (2009) also found that 61.5% of the brief intervention studies in their review excluded alcohol-dependent drinkers; thus, less is known about the natural course of drinking among heavy drinkers with more severe AUD.

As proposed by de Bruijn and colleagues (2006), the course of recovery from AUD may best be described as

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a “chronic relapsing disease” following AUD treatment, whereas periods of heavy alcohol use in the general population may follow a more favorable course. Our prior research on trajectories of drinking among those who receive alcohol treatment suggests that the course of recovery is indeed a discontinuous process (i.e., a chronic relapsing disease) whereby many individuals transition back and forth from abstinence to heavy drinking (Witkiewitz, 2008; Witkiewitz et al., 2010). Specifically, we have examined changes in drinking over time following treatment for an AUD using a variety of latent variable modeling techniques, and we have consistently found that latent Markov models (LMMs) provide the best fit to the observed data in comparison with other methods for studying trajectories over time (e.g., latent growth curve [LGC] models, latent growth mixture models [LGMM], multilevel models).

Importantly, the fit of empirical models to observed data provides information about theoretical models of change. Where “best fit” is estimated by the Bayesian information criterion (BIC; Schwarz, 1978), a relative fit index takes into account the log likelihood, sample size, and number of model parameters in determining which model provides the best fit to the observed data. LGC and multilevel models will provide the best fit when changes in drinking are relatively continuous (e.g., gradual decrease in drinking) and relatively homogenous across individuals (e.g., people are changing in the same ways over time). An LGMM will provide the best fit when changes in drinking are relatively continuous (e.g., gradual decrease in drinking) and heterogeneous across individuals (e.g., groups of individuals are changing in qualitatively distinct ways, with some increasing drinking and some decreasing drinking). Finally, an LMM will provide the best fit when changes in drinking are relatively discontinuous (e.g., sudden shifts in drinking at each assessment point).

As shown in Table 1, which provides a comparison of model fit for LGCs, LGMMs, and LMMs across four different studies of alcohol treatment outcome, the BIC is lowest (indicating the best-fitting model) for the LMM in all four studies. More details about the analyses for two of the four studies are provided in prior analyses of these data (Witkiewitz, 2008; Witkiewitz et al., 2010). Findings across these four studies provide strong evidence for discontinuous changes in drinking following treatment.

The goal of the current study was to extend this prior research to the study of drinking trajectories among heavy drinkers in the absence of any treatment or self-help and to evaluate de Bruijn and colleagues’ (2006) assertion that heavy drinkers who are non-treatment seeking may follow a more favorable course of alcohol use over time. If this assertion is correct, then we would hypothesize that an LGC model or LGMM would provide the best fit to the data, whereas if the “chronic relapsing disease” assertion is correct, we would hypothesize that the LMM would provide the best fit. Given the large number of individuals who engage

TABLE 1. Comparison of model fit (Bayesian information criterion [BIC]) in four treatment samples

Study	Sample size	Latent growth curve model BIC	Latent growth mixture model BIC	Latent Markov model BIC
Project MATCH ^a	1,726	32,082.9	30,560.7	28,609.3
COMBINE ^b	1,383	45,494.3	43,384.4	41,130.9
RREP ^c	563	18,938.9	17,786.5	17,042.9
UKATT ^d	742	19,855.6	19,628.6	18,956.5

Notes: Model fit based on BIC, where lowest BIC within each study is best-fitting model indicated by **bold** numbers. ^aProject MATCH (Matching Alcoholism Treatments to Client Heterogeneity) Research Group (1997), analyzed in Witkiewitz (2008); ^bCOMBINE (Combined Pharmacotherapies and Behavioral Interventions for Alcohol Dependence) Study Research Group (2003), as analyzed in Witkiewitz et al. (2010); ^cRREP (Relapse Replication and Extension Project), Lowman et al. (1996); ^dUKATT (United Kingdom Alcohol Treatment Trial) Research Team (2001).

in heavy drinking and never receive treatment, it is crucially important to gain a better understanding of the patterns of drinking changes in this group over time. Learning more about successful self-change attempts and reductions in heavy drinking among non-treatment seekers can inform and strengthen existing treatment strategies (Klingemann and Sobell, 2007) as well as inform the evaluation of brief intervention outcomes among non-treatment-seeking heavy drinkers.

Method

Participants and procedures

This study is a secondary analysis of a data set collected by Dearing and colleagues (2013), which resulted from the recruitment of participants via newspaper and radio advertisements in Buffalo, NY, for a study of alcohol attitudes among “moderate to heavy drinkers.” Study procedures have been described in detail previously (Dearing et al., 2013) and will only be summarized here. The Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993) was used to screen-in hazardous drinkers, defined as those with an AUDIT score of 8 or above for men ages 65 years and younger, 7 or above for men older than 65 years, and 7 or above for women (Babor et al., 2001). To be included in the study, participants had to be at least 18 years of age, not be enrolled in any alcohol or other drug treatment (including self-help meetings) in the past year, have no evidence of severe cognitive impairment, and have no symptoms of an active psychotic disorder or current mood disorder with psychotic features.

Those who were eligible and provided valid data ($n = 208$) completed the baseline assessment in person. Follow-up assessments were completed at home and returned by mail at 6 months (80.3% returned), 12 months (75.0% returned), 18 months (74.0% returned), and 24 months (74.5% returned).

All study procedures were approved by the appropriate institutional review board, and all participants provided informed consent.

Participants in the current analyses ($n = 151$) were those individuals who did not seek any form of professional treatment (including detoxification services, inpatient or outpatient treatment, mental health counselor, emergency room, or primary care services for alcohol use) or self-help (e.g., Alcoholics Anonymous [AA], Internet groups) during the 2 years of the study. Using these criteria, we excluded 29 people because they received treatment during the 2 years of the study (13.9% of 208), and we excluded 26 people because they were missing data on the help-seeking variables (12.5% of 208). Thus, the current study was based on a subsample of 151 individuals (72.6% of 208). Before the study, 88.3% of these 151 individuals had never received treatment, and 85.4% had never attended AA or other self-help groups. The individuals who received treatment during the 2 years of the study and were excluded from the current analyses had significantly higher AUDIT (Saunders et al., 1993) scores, $F(1, 178) = 21.02, p < .001$, drank significantly more frequently at the baseline assessment based on percentage of drinking days, $F(1, 178) = 5.11, p = .025$, and were more likely to meet criteria for an AUD diagnosis (see below). The groups did not significantly differ in drinking frequency or intensity during the first 6 months of the study, percentage of drinking days: $F(1, 163) = 1.78, p = .18$; drinks per drinking day: $F(1, 163) = 0.13, p = .72$; and percentage of heavy drinking days: $F(1, 163) = 0.66, p = .42$.

The individuals in the subsample of those who did not seek treatment ($n = 151$) included 77 women (51.0%), and the average age among all participants was 36.71 years ($SD = 12.96$). Most participants were White (73.5%) or African American (21.2%); other participants self-identified as being Asian (0.8%), Native American (1.3%), or "other" (3.3%). Four percent of the sample was Hispanic or Latino. Most participants were either single/never married (46.4%) or married (24.5%), and others were separated/divorced (19.8%), cohabitating (7.9%), or widowed (1.3%). The average level of education was 13.69 years ($SD = 2.96$), and 64.7% of the sample was employed at least part time.

Measures

Diagnostic assessment. AUD was assessed using the Computerized Diagnostic Interview Schedule for DSM-IV (Robins et al., 1988, 2000). Of the participants in the current analyses, 75 (49%) met criteria for a current (past-year) AUD as indicated by the *Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition* (DSM-IV; American Psychiatric Association, 1994), which was significantly different from the 69% who met the AUD criteria among those who sought treatment during the study, $\chi^2(1) = 3.88, p = .049$. Given this discrepancy, as well as the differences

between those who sought treatment on other measures of alcohol use severity (e.g., AUDIT, described above), we included current AUD diagnosis as a covariate in all models.

Alcohol use. The Timeline Followback (TLFB; Sobell and Sobell, 1992) was used to assess daily drinking data (standard drink equivalents) during the 6 months before each assessment. At baseline, the TLFB was administered as an interview, and at subsequent assessments participants provided daily drinking data using calendars filled out at home and returned by mail. TLFB data were used to compute a summary variable indicative of proportion of heavy drinking days (PHD; i.e., ≥ 5 drinks per day for men, ≥ 4 drinks per day for women).

Statistical analyses

All models were estimated with Mplus Version 7 (Muthén and Muthén, 2012) using a robust maximum likelihood estimator. The drinking outcome used in the models described below was the proportion of heavy drinking days in the past 6 months (range: 0–1.00, with 1.00 indicating 100% heavy drinking days), which was square root transformed before analyses to address the positive skew of the outcome. This outcome was chosen because prior research with treatment samples has used PHD as the primary outcome (Witkiewitz et al., 2010). Therefore, the results of this study can be compared more easily with those of treatment studies.

To examine drinking trajectories over time, we tested three different longitudinal latent variable models: LGCs, LGMMs, and LMMs. Each model provides a unique characterization of the observed data, which can be informative for describing the type of change. The best model among the three types of models was determined using the BIC (Schwarz, 1978), which, as stated earlier, is a relative fit index that takes into account the log likelihood, sample size, and number of model parameters in determining which model provides the best fit to the observed data.

The LGC model provides estimates of average change over time as well as individual variability around mean changes. Specifically, for each individual in the sample, we estimated an intercept (i.e., initial level) and slope (i.e., change) of PHD across the 2-year period. We then calculated the mean of all individual intercepts and slopes as well as the random variance around the mean intercept and slopes. Different LGC models with different assumptions about the functional form of change over time (i.e., quadratic, cubic change) were estimated. Models with nonsignificant chi-square values, root mean square error of approximation (RMSEA; Browne and Cudeck, 1993) less than .06, and comparative fit index (CFI; Bentler, 1990) greater than .95 were considered a good fit to the observed data (Hu and Bentler, 1999).

The LGMM is an extension of the LGC model that incorporates a categorical latent variable (i.e., latent class

variable) as a higher order factor. Similar to the LGC, each individual has a unique growth curve (defined by an intercept and slope) as well as random variance around the mean growth curves. However, instead of one mean growth curve (as in the LGC), we characterize the heterogeneity in growth curves across individuals by a finite number of trajectory classes. The number of classes was determined by multiple indices: BIC (Schwarz, 1978), the Bootstrapped Likelihood Ratio Test p value (BLRT; Lo et al., 2001; Nylund et al., 2007), classification precision (defined by entropy, a summary measure of the estimated posterior class probabilities), and interpretability of latent classes.

The LMM also uses categorical latent class variables to examine change over time, but the LMM does not use the LGC model as the measurement model (as in LGMM). Rather, LMM incorporates multiple latent class variables to estimate the probability of transitioning between discrete states (i.e., latent classes) across time (Böckenholt, 2005). First, latent profile models (i.e., latent class models) of PHD were estimated for each assessment point using the BIC, BLRT, and classification precision to pick the number of classes for each point in time. Second, we combined the latent profile models for each assessment point using the LMM, which included the estimation of the transition probabilities between adjoining latent classes across time.

Results

At the baseline assessment, the average PHD was 0.39 ($SD = 0.29$), and all participants reported at least one heavy drinking day during the pre-baseline period. At the first follow-up, 6 months after baseline, 97.2% of participants reported at least one heavy drinking day, and the average PHD was 0.32 ($SD = 0.27$). At the 12-month and 18-month follow-ups, 96% reported at least one heavy drinking day during the prior 6 months, and the average PHD decreased to 0.29 ($SD = 0.27$) at 12 months and 0.27 ($SD = 0.25$) at the 18-month follow-up. At the 24-month follow-up, 90% reported at least one heavy drinking day, and the average PHD decreased to 0.25 ($SD = 0.27$).

Latent growth curve models

The LGC model with a quadratic effect provided a good fit to the data based on CFI (CFI = .99); chi-square, $\chi^2(8) = 14.61$, $p = .07$; and RMSEA (RMSEA = .07, 90% CI [0.00, 0.13]). The BIC was -455.10. The average intercept was 0.496 (representing 0.246 PHD in the untransformed metric) with a significantly negative linear slope ($B [SE] = -0.16 [0.07]$, $p = .02$) and nonsignificant quadratic slope ($B [SE] = 0.03 [0.07]$, $p = .67$), indicating a stable decrease in PHD over time. AUD diagnosis predicted a significantly higher intercept (i.e., PHD at baseline; $\beta = .33$, $p < .001$) but did not significantly predict the linear or quadratic slopes.

Latent growth mixture models

To determine the optimal class solution for the LGMM, we tested a two-class model (BIC = -488.65; BLRT = 51.41, $p < .0001$), a three-class model (BIC = -505.57; BLRT = 36.99, $p < .0001$), and a four-class model (BIC = -498.74, BLRT = 13.24, $p = .09$). The three-class model provided the best balance of parsimony and model fit, with a significant improvement in fit over the two-class model (based on the significant BLRT p value).

The classification quality of the three-class LGMM was acceptable (entropy = 0.92), and there was clear distinction between classes (average latent class probabilities for most likely class ranged from .91 to .97). As seen in Figure 1, which provides the untransformed PHD over time by class, the three classes could be described as (a) a stable, decreasing heavy drinking class (~80.2% of the sample); (b) a frequent heavy drinking class with a very slight reduction in frequent heavy drinking over time (~9.7% of the sample); and (c) a class that showed a sharp reduction in the frequency of heavy drinking with a slight increase in frequency of heavy drinking over time (~10.1% of the sample). As with the LGC model, AUD diagnosis predicted the intercept ($\beta = .34$, $p < .001$) but did not significantly predict the linear or quadratic slopes.

Latent Markov models

Before estimating the LMM, we conducted a latent profile analysis of PHD at each time point. Across nearly all time points, the three-class models yielded significant improvements in fit over the two-class models, and the four-class models did not significantly improve fit over the three-class models. For all time points, the three classes could be described as occasional heavy drinking (average untransformed PHD = 0.31; approximately 50% of the sample at all time points), infrequent heavy drinking (average untransformed PHD = 0.05; approximately 43% of the sample), and very frequent heavy drinking (average untransformed PHD = 0.85; approximately 7% of the sample).

The LMM was then estimated to examine the transitions between these three latent classes across time points. The model had reasonably good classification precision based on entropy = 0.91, but the BIC indicated a much poorer fit than the LGMM and LGC models (BIC = -342.88). Latent transition probabilities (P) indicated a high degree of stability within classes; for example, the probability (P) of remaining classified as an infrequent heavy drinker was 1.00 from baseline to 6 months, 1.00 from 6 to 12 months, .98 from 12 to 18 months, and .95 from 18 to 24 months. The most likely transitions across time were from frequent to occasional heavy drinking ($P = 0.36$ from baseline to 6 months), from frequent to infrequent heavy drinking ($P = 0.14$ from 12 to 18 months), and from occasional to infrequent heavy

FIGURE 1. Estimated trajectories for three-class latent growth mixture model of proportion of heavy drinking days among non-treatment seekers ($n = 151$)

drinking ($P = 0.14$ from 18 to 24 months). AUD diagnosis predicted a significantly lower probability of being assigned to the infrequent heavy drinking class (odds ratio = 0.14, $p = .001$) than to the frequent heavy drinking class. AUD diagnosis did not significantly differentiate membership in the occasional and frequent heavy drinking classes.

Model comparison

Using the BIC to compare model fit, the three-class LGMM produced the lowest BIC (BIC = -505.57), indicating a better fitting model than the LGC model (BIC = -455.10), the alternative LGMM (two-class: BIC = -488.65; and four-class: BIC = -498.74), and the LMM (BIC = -342.88).

Discussion

This study examined drinking trajectories among non-treatment-seeking heavy drinkers over the course of 2 years. Consistent with prior studies (de Bruijn et al., 2006) and prior analyses of the data used in this study (Dearing et al., 2013), heavy drinkers who did not receive any treatment showed significant reductions in heavy drinking over time. Importantly, continuous latent growth models, including LGC and LGMM, provided a much better fit to the observed data than the discontinuous model (LMM),

a finding that is quite different than that of prior studies of heavy drinkers who received alcohol treatment (Witkiewitz, 2008; Witkiewitz et al., 2010). As shown in Table 1, we have previously found that LMM provides a much better fit to drinking trajectories among individuals who receive alcohol treatment.

These models shed light on the course of drinking changes among non-treatment-seeking heavy drinking adults recruited from the community. Specifically, the results from the LGMM in this study indicated that most individuals reduced the frequency of their heavy drinking over time, even in the absence of formal or informal (i.e., mutual help, self-help, pastoral counseling) types of treatment. As shown in Figure 1, the majority of individuals (~80.2%) reduced their heavy drinking from nearly 30% of days to fewer than 20% of days, and approximately 10.1% of the sample showed major reductions in the frequency of heavy drinking from more than 80% of days to just less than 40% of days 2 years later. Further, only a small percentage of individuals (~9.7%) maintained very high levels of frequent heavy drinking.

We also considered one covariate in the analyses, AUD diagnosis, which was included as a measure of severity given prior claims that individuals with more severe dependence on alcohol may be less likely to have successful self-change attempts (Dawson et al., 2005). Across models, we found that AUD diagnosis predicted more frequent heavy drink-

ing initially, but it did not predict change in heavy drinking frequency over time. This suggests that reductions in heavy drinking over time are not significantly associated with meeting criteria for an AUD and perhaps that individuals with more severe problems are also capable of self-change (Klingemann et al., 2010). It also calls into question the decision of many brief intervention studies to exclude individuals with alcohol dependence from participation in those trials.

As noted in Jenkins and colleagues (2009), 61.5% of the 26 brief intervention studies they reviewed had excluded alcohol-dependent drinkers. Yet the results from the current study suggest that even individuals with AUD are capable of reducing heavy drinking over time and that although more intensive treatment would be indicated for more severe heavy drinkers, it is also the case that brief interventions may be beneficial for this population.

Limitations

This study had several limitations. First, the sample consisted of heavy drinkers who responded to an advertisement for “moderate to heavy” drinkers, which would suggest some problem recognition. Indeed, 20.8% of the sample indicated current concern about their drinking, 15.4% identified as a current problem drinker, and 16.6% indicated that it was “very likely” that they would reduce their amount of drinking without help in the next 2 years. The initial reduction in frequent heavy drinking from baseline to the 6-month follow-up, observed across all models, could suggest either regression to the mean level of heavy drinking among drinkers, reactivity to enrolling in the study, or assessment reactivity due to reporting on drinking and drinking-related variables (Clifford and Maisto, 2000; Maisto et al., 2007).

Second, we do not know whether changes in drinking were sustained beyond the 2-year assessment period. Third, the sample did include some individuals (<15%) who sought treatment or informal help in the past (although not in the past year), and it could be the case that prior engagement with treatment and informal help could be related to reductions in heavy drinking. However, previous analyses of these data showed that prior treatment and history of self-help group attendance were unrelated to changes in drinking over time (Dearing et al., 2013).

There are also strengths and limitations of each modeling approach used in the current study. The primary strengths of all three modeling approaches include the integration of person-centered and variable-centered approaches to examine patterns of change over time (Muthén and Muthén, 2000) and the accommodation of missing data by using maximum likelihood estimation under the assumption that data were missing at random (Schafer and Graham, 2002).

There are also limitations. Mixture models have elicited different views about their utility in the area of quantitative

methods, and caution is warranted in the interpretation of mixture models (Bauer and Curran, 2004). Some concerns about mixture modeling include the tendency for overextraction of latent classes, reification of groups that do not exist, and the loss of power due to artificially dividing growth trajectories into latent classes (Bauer and Curran, 2003).

Public health implications

In most countries in the world, the majority of individuals who are heavy drinkers do not seek or receive treatment for heavy alcohol use. Although there are many barriers to receiving treatment (Saunders et al., 2006; Tucker and Simpson, 2011), it is also the case that most individuals who engage in heavy alcohol use fail to seek treatment because they do not perceive a need for treatment (Edlund et al., 2009; Mojtabai and Crum, 2013; Moss et al., 2010). Other individual-level barriers include believing that one should be able to handle the problem without professional help, not having the motivation to stop drinking, and beliefs that treatment would not be beneficial (Saunders et al., 2006).

We hypothesized that these person-related barriers have been perpetuated (or even formed) by the notion that AUDs are characterized by a chronic relapsing pattern, that the only way to recover from an AUD is via treatment (or mutual-help organizations), and that recovery requires abstinence. The results from the current analyses and prior studies show that heavy drinkers (including those with AUD) do significantly reduce the frequency of heavy drinking over time, that these reductions can occur unassisted, and that moderate-drinking recoveries are quite possible (Dawson et al., 2005; Dearing et al., 2013; Klingemann et al., 2010; Tucker and Simpson, 2011).

The alcohol research and treatment community has much to learn from these individuals. It is also the case that treatment providers, policy makers, and the general public may benefit from the knowledge that many individuals who engage in heavy drinking are capable of nonheavy drinking, even in the absence of treatment. Finally, the results from this study provide a reference group for brief intervention studies of non-treatment-seeking heavy drinkers and suggest that the magnitude of self-change among heavy drinkers sets a fairly high bar for the effect sizes needed in brief intervention studies in order to demonstrate an effect on drinking reduction.

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