Published in final edited form as:

Drug Alcohol Rev. 2015 May ; 34(3): 242–251. doi:10.1111/dar.12230.

Pathways to change: Use trajectories following trauma-informed treatment of women with co-occurring post-traumatic stress disorder and substance use disorders

TERESA LÓPEZ-CASTRO[1], **MEI-CHEN HU**[3], **SANTIAGO PAPINI**[1,2], **LESIA M. RUGLASS**[1], **DENISE A. HIEN**[1,2,3]

[1]Department of Psychology, The City College of NewYork—CUNY, NewYork City, USA,

[2]NewYork State Psychiatric Institute, Columbia University Medical Center, NewYork City, USA,

[3]Department of Psychiatry, Columbia University College of Physicians and Surgeons, NewYork City, USA

Abstract

Introduction and Aims.—Despite advances towards integration of care for women with co-occurring substance use disorder (SUD) and post-traumatic stress disorder (PTSD), low abstinence rates following SUD/PTSD treatment remain the norm. The utility of investigating distinct substance use trajectories is a critical innovation in the detection and refining of effective interventions for this clinical population.

Design and Methods.—The present study reanalysed data from the largest randomised clinical trial to date for co-occurring SUD and PTSD in women (National Drug Abuse Treatment Clinical Trials Network; Women and Trauma Study). Randomised participants (n = 353) received one of two interventions in addition to treatment as usual for SUD: (i) trauma-informed integrative treatment for PTSD/SUD; or (ii) an active control psychoeducation course on women's health. The present study utilised latent growth mixture models (LGMM) with multiple groups to estimate women's substance use patterns during the 12-month follow-up period.

Results.—Findings provided support for three different trajectories of substance use in the post-treatment year: (i) consistently low likelihood and use frequency; (ii) consistently high likelihood and use frequency; and (iii) high likelihood and moderate use frequency. Covariate analyses revealed improvement in PTSD severity was associated with membership in a specific substance use trajectory, although receiving trauma-informed treatment was not. Additionally, SUD severity, age and after-care efforts were shown to be related to trajectory membership.

Discussion and Conclusions.—Findings highlight the necessity of accounting for heterogeneity in post-treatment substance use, relevance of trauma-informed care in SUD recovery

Teresa López-Castro PhD, Assistant Professor, Mei-Chen Hu PhD, Research Scientist, Santiago Papini MA, Research Fellow, Lesia M. Ruglass PhD, Assistant Professor, Denise A. Hien PhD, Professor. Correspondence to Dr Teresa López-Castro, Department of Psychology, The City College of NewYork—CUNY, 160 Convent Avenue, NAC Building, Rm 7/120, NewYork City, NY 10031, USA.Tel: +212 650 8965; Fax: +212 650 8910; tlopezcastro@ccny.cuny.edu.

Conflict of interest

The authors have no conflict of interests to declare.

and benefits of incorporating methodologies like LGMM when evaluating SUD treatment outcomes. [López-Castro T, Hu M-C, Papini S, Ruglass LM, Hien DA. Pathways to change: Use trajectories following trauma-informed treatment of women with co-occurring post-traumatic stress disorder and substance use disorders. *Drug Alcohol Rev* 2015]

Keywords

substance abuse; post-traumatic stress disorder; substance use trajectory; latent growth mixture modelling; relapse

Introduction

It is estimated that over 80% of women who seek treatment for substance abuse have lifetime histories of sexual and/or physical victimisation [1]. Women with trauma histories and substance use disorders (SUDs) are likely to have more severe and complex clinical presentations, are more difficult to engage and retain in SUD treatment, relapse to substance use faster and have generally poorer SUD outcomes than their nontraumatised counterparts [2].

To address these complications of SUD/post-traumatic stress disorder (PTSD) comorbidity, interventions have emerged that incorporate cognitive behavioural therapies for trauma into substance abuse interventions [3–5]. To date, the largest of these trials was conducted through the National Drug Abuse Treatment Clinical Trials Network (NIDA CTN) and provided 353 women with co-occurring SUD and PTSD with add-on trauma-informed care as a means of improving SUD treatment retention and outcomes [6]. Despite significant reduction in PTSD severity, no overall effects of time or treatment were found on SUD outcomes. These results are evidence of the heterogeneity and chronicity of SUDs in the face of multiple treatment efforts, a common finding in addiction research (e.g. Project MATCH). Because relapse remains the modal outcome in follow ups of intervention trials for SUD, variability in SUD treatment response, distinct trajectories of substance use in follow-up periods and barriers to the recovery process in co-occurring SUD and PTSD stand as crucial areas of investigation.

Findings of high rates of relapse, heterogeneity and non-linearity in substance use following treatment [7–10] have underscored the need for clinical research to move beyond solely binary (abstinent or relapsed) models of SUD outcome and examine longitudinal trajectories of growth or decline. One alternative to linear regression models is latent growth mixture modelling (LGMM), which can account for heterogeneity within a population and integrates person- and variable-focused variables known as *latent classes*, LGMM detects the presence of different types of trajectories in the population in conjunction with individual growth patterns (vs. chance variations within each trajectory) [11,12].

Prior trajectory-based modelling in alcohol and substance abusing samples has demonstrated that recovery and relapse processes are distinctly variable between individuals. Group-based approaches have been employed to empirically validate distinct developmental courses of substance abuse [13,14] as well as specific trajectories following treatment in alcohol abusing samples [12,15,16]. Modelling heterogeneity in co-occurring SUD and PTSD

treatment is in its nascent stages but has already begun to highlight meaningful differences in how individuals interact and respond to intervention efforts. A recent examination of heterogeneity in attendance patterns employing latent class pattern mixture modelling suggests that some clients self-titrate trauma-focused treatment to positive effect on substance use outcomes [17]. However, no research to date has applied a group-based modelling technique to consider the critical issue of variability in post-treatment substance use of co-occurring SUD and PTSD. To this end, the current study conducted a secondary analysis of the NIDA CTN-0015 Women and Trauma Study (WTS) data with the aim of identifying differential patterns of substance use during the 12 months following treatment and represents the first attempt to utilise LGMM to analyse heterogeneity in the substance use outcomes of women with this comorbidity. A second aim was to examine the potential association between each trajectory to pretreatment risk factors, treatment response and post-treatment behaviours.

Method

The present study utilised data from the multisite randomised trial of psychosocial treatments for 353 women with co-occurring PTSD and SUD conducted by NIDA CTN. A detailed description of the WTS method was provided in a previous publication [6]. The WTS utilised a randomised, controlled, repeated measures design to evaluate the effectiveness of Seeking Safety [18] in conjunction with treatment as usual substance abuse services compared with an active treatment control group, Women's Health Education.

Participants

Eligible women met current Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR) diagnosis of alcohol or drug dependence and used alcohol or a drug in the prior 6 months. Additionally, women had to report at least one lifetime traumatic event and meet DSM-IV-TR criteria for either full PTSD or subthreshold PTSD. A total of 353 women from outpatient, community-based substance abuse treatment programs met all eligibility criteria and were randomised into the study. Participants were diagnosed with cocaine (70.5%), alcohol (56.1%), marijuana (27.2%) or opioid dependence (25.6%). Table 1 provides demographic and clinical characteristics of the sample.

Measures

Assessments were collected at baseline and following treatment at 1 week, 3 months, 6 months and 12 months.

SUD diagnosis and identification of primary problematic substance were assessed at baseline with the Composite International Diagnostic Interview for DSM-IV [19]. The percentage of days of alcohol or drug use in the past 30 days was calculated from the Addiction Severity Index Lite [20].

The Clinician-Administered PTSD Scale (CAPS) [21] assessed PTSD diagnosis and severity at baseline and all post-treatment visits. Significant reduction in PTSD severity was quantified as a decrease of 30 points or more on the CAPS score [22].

Data analysis

LGMM was used to identify substance use trajectories in the year following treatment. The main outcome variable was the percentage of days of use in the past 30 days of the primary problematic substance (based on baseline dependence measure).

Mplus

Mplus version 6.5 [23] was used to conduct the LGMM analyses. Mplus employs maximum likelihood estimation with the expectation maximisation algorithm to model continuous outcome variables with missing values. To address the challenges in identifying global maximum rather than local optima in mixture models, Mplus supplies automatically generated starting values with random perturbations. Following Hipp and Bauer's [24] recommendations, 100 random sets with 50 full optimisations were employed to increase the estimation power of the mixture models.

Model construction

Unconditional models for the substance use outcome (percentage of days used in the past 30 days) were built by the systematic increase of the number of classes (i.e. one through five-class models) and associated growth factors (i.e. linear and quadratic terms). A substantial number of participants were not using at any one follow-up point (61% abstinent at 1-week following treatment, 56% abstinent at 3 months, 46% abstinent at 6 months and 47% abstinent at 12 months post-treatment), but only a minority (6.6%) reported abstinence at all four follow-up points. Consistent with prior research [25], a two-part modelling strategy (u- and y-part) that simultaneously captures both use/non-use likelihood and use frequency was applied. The u-part consisted of a latent class growth analysis of the probability of use or non-use. The y-part involved growth mixture modelling of the frequency of use among those categorised as users in the u-part. In the two-part model, logistic growth model estimations of binary indicators were measured alongside growth models for the continuous outcomes of those using at the time of measurement.

Model estimation

Bayesian information criterion (BIC) [26] and the adjusted likelihood ratio test (aLRT) were used to assess model fit [27]. The BIC measures a model's relative fit on the basis of a function of its log-likelihood value; the log-likelihood value takes into account both the model's fit to the observed data as well as the model's complexity. The aLRT tests a model (k) against a model with one less class (k-1); a significant P value suggests better fit of the k model. Classification precision was evaluated by the entropy statistic [28], which estimates the probability of an individual's class membership. Entropy values range from 0 to 1.0, with numbers closer to 1.0 indicating more classification accuracy. Overall, the best relative fit model would have the lowest BIC, a significant Lo–Mendell–Rubin (LMR) P value and the highest entropy.

Of the 353 randomised participants, 288 attended at least one follow up, allowing for inclusion in the unconditional models. Posterior probability-based multiple imputation was utilised for time points with missing outcome variable data. Of these 288 participants, 20 were missing covariates and could not be included in the final conditional models (missing

covariates were not imputed). Pattern analyses indicated there were no significant associations between missingness and variables (including covariates) in the models, suggesting data were missing at random. Under this assumption, Mplus's estimation procedure provides good estimates of model parameters directly based on all available data.

After arriving at the unconditional growth two-part mixture model with the best fit, conditional two-part growth mixture modelling was employed in order to (i) reduce model misspecification and (ii) identify variables significantly associated with membership in each class. The conditional two-part models consisted of the re-estimation of the unconditional models with the incorporation of covariates that were selected on the basis of strong association to SUD/PTSD treatment outcomes in prior research [29–31]. Controlling for these covariates on growth factors and class memberships improved specification of class membership estimates. Selected covariates were bivariately fit across each of the three latent classes to assess associations with particular class membership utilising the Wald test of equality of means across latent trajectory classes [32,33].

Results

Consistent with previous research [10,34,35], the u-part and y-part of the two-part models were assessed separately for class and growth functions to increase accuracy of fit. Table 2 provides the fit statistics for all models.

Unconditional growth mixture models

The two-class solution (with slope and intercept variances constrained to zero) afforded the best fit for the unconditional u-part model. The two latent classes were identified as: (i) high probability of use; and (ii) low probability of use. Class proportions were 55.1% and 44.9%, respectively.

For the unconditional y-part modelling, the three-class estimate provided the best fit because of the three-class model's BIC (197.399), adjusted LMR ratio test (aLRT = 45.760, $P = 0.0097$) and entropy (0.737). The variances of the three-class model's intercept, linear and quadratic slopes were fixed.

The two-part modelling was comprised of a u-part model of likelihood of use (with no variances in intercept and slope) and a y-part model (with class-equal variances in intercept and no variances in slope and quadratic terms) of use during the post-treatment year. On the basis of its BIC, significant aLRT and entropy, the three-class model provided a better fit than the one- or two-class models to the observed data in the analysis of unconditional two-part model estimations (Table 2). The two-part model (Figure 1) incorporated both propensity for use as well as frequency of use in the post-treatment year in three distinct trajectories: a *low risk/infrequent use* group (50.5%) with a low likelihood for use [estimated probability = 0.22, SE = 0.05, $P < 0.001$] and an estimated mean 4 days of use per month by 12-month follow up; a *high risk/infrequent use* group (26.6%) with a high likelihood for use (estimated probability = 0.77, SE = 0.08, $P < 0.001$) and fewer than 6 days of use per month by 12-month follow up; and a *high risk/frequent use* group (22.9%) with high likelihood of

use (estimated probability = 0.99, SE = 0.02, $P < 0.001$) and use increasing to nearly daily by 12-month follow up.

Conditional growth mixture models

A conditional two-part modelling estimation was performed to evaluate the role of specific covariates in predicting membership to each of the three estimated classes. The distribution of covariate means and equality of means across classes are shown in Table 3. Table 4 depicts the prevalence of the seven covariates in each of the three classes.

Class membership was not correlated to treatment condition nor history of prior substance abuse treatment. Membership in the *low risk/infrequent use* class was associated with the covariates of age, baseline amount of primary substance use, change in CAPS score from baseline to 1 week following treatment and substance use post-treatment. Women in the *low risk/infrequent use* class were younger and had less use in the 30 days prior to the beginning of the study when compared with the *high risk/infrequent use* [adjusted odds ratio (AOR) = 0.07] and the *high risk/frequent use* classes (AOR = 0.05). Women who continued in substance abuse treatment programs during the follow-up period of the study were more likely to follow a trajectory of fewer lapses and decreased use in the year following treatment rather than the *high risk/infrequent use* (AOR = 1.86) and *high risk/frequent use* (AOR = 0.55) trajectories. Women who demonstrated improvement in their PTSD symptoms were more likely to have a *low risk/infrequent use* trajectory rather than a *high risk/infrequent use* (AOR = 0.97) or *high risk/frequent use* (AOR = 1.02) pattern.

There was no significant difference in reduction of PTSD severity between *high risk/infrequent use* and *high risk/frequent use* trajectories. Women in the *high risk/infrequent use* tended to be significantly older (AOR = 0.89) than those in the *high risk/frequent use* class.

Discussion

This study marks the first application of LGMM to investigate post-treatment substance and alcohol use trajectories in women dually diagnosed with PTSD and SUD. Findings supported a three-class trajectory model of post-treatment use patterns. The detection of three distinct subgroups (*low risk/infrequent use, high risk/infrequent use* and *high risk/frequent use*) echoes findings from previous research that have modelled alcohol and substance use with LGMM techniques [34,36,37] and provides further confirmation of the presence of clinically significant subgroups in the recovery process.

The present findings document the heterogeneity of SUD treatment responses, better understood as consisting of distinct subgroups rather than a binary—abstinent or relapsed—categorisation. This study's three-class model indicated that half of the sample was comprised of a *low risk/infrequent use* class, characterised by both a low likelihood of use post-treatment and when using, doing so at a low frequency (estimated 5 days per month). A second class in this model depicted the trajectory of women with a high likelihood for use in the post-treatment year but infrequent use following lapses. The third estimated group consisted of women who similar to the *high risk/infrequent use* group were very likely to resume using their primary substance but when they did so, used frequently.

In previous studies, growth-centred investigations have encountered an ‘inconsistent’ substance use subgroup in which its members’ behaviour tended towards the unpredictable [10,38]. This trajectory may represent an ‘unstable’ or in flux state within the recovery process in contrast to the consistency of the frequent/infrequent use. If recovery from SUD is understood as a discontinuous change process towards a state of equilibrium (be it consistent use or no use), inconsistent use may represent an individual’s oscillation between relapse and abstinence. The lack of support for this ‘inconsistent’ class in the current study and further, the quantitative stability found in the study’s *high risk/infrequent use* class suggest the presence of an important addition to the traditional, binary conceptualisation of SUD outcome as either ‘recovered’ (i.e. abstinent/minimal use) or ‘relapsed’.

We aimed to heighten the interpretive power of a trajectory-based approach by addressing specific variables in the lives of participants that may predict membership in one of the three distinct growth classes. This study promotes the understanding of SUDs from a chronic disorder perspective [39]. As such, after- and continuing-care efforts for improvement of symptoms and maintenance of gains are considered critical [40]. Findings from the current analysis support the applicability of after-care/maintenance treatment for this population: women in the *low risk/infrequent use* group reported more contact with substance abuse programs following the active treatment than women in the two *high risk* for use trajectories. However, studies have demonstrated that both formal and informal after-care efforts can bolster the efficacy of SUD treatments [41,42]. The observed relationship between minimal likelihood/low use frequency in recovery and continued care underscores both the relevance of a chronic disorder perspective and the step-wise, multi-determined pattern of recovery. The *low risk/infrequent use* trajectory underscores the dynamic nature of recovery where more motivation may lead to more treatment that in turn lead to more gains and more motivation.

Findings highlight the benefit of multiple treatment episodes and the relevance of adopting a broader, ‘long-range’ lens that acknowledges the impact of repeated exposure to treatment. In the present study, the SUD treatment careers [43] of women played a significant role in which post-treatment use trajectory they would ultimately follow. These results emphasise that for addictive disorders, intervention efforts are best understood as potentially interactive, incremental and cumulative events.

In our finding that women who reduced their PTSD symptoms during treatment were better able to manage their substance use in the year following treatment, this study highlights the importance of PTSD symptom amelioration for women in substance use recovery as well as reinforces a body of literature that has sought to justify the concurrent treatment of PTSD and SUD [44–47]. For women in the *low risk/infrequent use* class, the reduction of PTSD symptoms may have lessened the urge to self-medicate through substances during the post-treatment year. The link between PTSD and SUD symptom change may also be influenced by the phenomenological similarities of both disorders [48]. In contrast to the power of PTSD symptom change to classify trajectory membership—significantly distinguishing *low risk/infrequent use* from the two other subgroups—neither the severity nor chronicity of women’s PTSD symptoms at the outset of treatment predicted classification in any of the three trajectories of post-treatment substance use. The extent to which PTSD and SUD

reinforce and mitigate one another appears to vary widely and is very likely subject to a multitude of contextual variables. This study provides further justification for integrated treatments that target PTSD symptoms and substance use concurrently. For clinicians, this may translate into further assurance that interventions for PTSD will not negatively impact SUD treatment, but may very well reduce the need of patients to use substances for self-medicating purposes.

The study's findings challenge the persistent and widely held belief that equates substance use following SUD treatment with treatment failure. Instead, LGMM analyses showed that more than one recovery path was available to women who used after being treated for SUD. The women in the present study behaved in a style consistent with Marlatt and Gordon's [49] relapse prevention model. Findings indicated that women were either at a high or low likelihood of use post-treatment. Despite their level of risk, if they were to use, relapse was not a given. Instead, most women in the study were likely to use infrequently after what Marlatt and Gordon term a 'lapse'.

As the first study to explore trajectories in this population of alcohol and substance users, we accounted only for the number of use days of the primary problematic substance in the past month. Future studies may address such limitation by incorporating polysubstance use and investigating changes not only in frequency but in quantity of use and changes in drug class. The sole reliance on a retrospective self-report measure for the study's main outcome measure represents another potential limitation. In conjunction with simple recall errors, the bias inherent in self-report measures has been well documented [50]. Future research should consider incorporating corroborating objective measures of use (e.g. breathalyser and urine samples) and innovations in real-time assessment such as ecological momentary assessment methods [51]. The present study elected to examine substance types in aggregate in order to account for the relatively small total sample size as well as the limited prevalence of use of some of the substance types. Despite research indicating the salience of similar recovery trajectories across substances [52], future research must systematically inves tigate the number and quality of fit of trajectory models by drug class and type to test the generalisability of a three-class model.

Although LGMM research has been conducted with smaller sample sizes [36,38], the size of the current sample may have restricted the ability to identify additional growth patterns; with a larger number of participants, the detection of a fourth pattern, as documented in a number of LGMM substance studies [53–55], may have been possible. A limitation noted in the use of LGMM is its inability to empirically conclude the 'true' number of classes within a sample—and whether such a correct number exists in [56]. In the current study, the single-class model exhibited enough variance in its growth parameters to merit reanalysis within a latent growth mixture model. Future investigations of trajectories of substance use must incorporate both empirical and theoretical findings when hypothesising trajectories and take heed of both the limitations and benefits of LGMM.

For women dually diagnosed with PTSD and SUD, the current study established the presence of several varied clinical presentations linked to substance use following treatment, each with potentially different needs, vulnerabilities and strengths. Results highlight

opportunities for tailoring interventions to the specific clinical presentation and the potential impact of these choices on a woman's trajectory of recovery. Analyses demonstrate that a 'one-size-fits-all' approach may be of limited value for this population. Rather, when considering treatment type, intensity and frequency, attention to factors such as a woman's severity of use at the onset of treatment, previous exposure to treatment and PTSD symptomatology will likely mean the difference between membership in a positively oriented or negatively oriented course of recovery.

Acknowledgement

The research reported in this article was supported by a grant from the National Institute on Drug Abuse: U10 DA13035 (Edward Nunes, PI). The Clinical Trial Identification Number is NCT00078156 (NIDA).

References

[1]. McHugo GJ, Caspi Y, Kammerer N, et al. The assessment of trauma history in women with co-occurring substance abuse and mental disorders and a history of interpersonal violence. J Behav Health Serv Res 2005;32:113–27. [PubMed: 15834262]

[2]. Brady KT, Dansky BS, Sonne SC, Saladin ME. Posttraumatic stress disorder and cocaine dependence. Order of onset. Am J Addict 1998;7:128–35. [PubMed: 9598216]

[3]. Donovan B, Padin-Rivera E, Kowaliw S. 'Transcend': initial outcomes from a posttraumatic stress disorder/substance abuse treatment program. J Trauma Stress 2001;14: 757–72. [PubMed: 11776422]

[4]. Back SE, Waldrop AE, Brady KT. Treatment challenges associated with comorbid substance use and posttraumatic stress disorder: clinicians' perspectives. Am J Addict 2009;18:15–20. [PubMed: 19219661]

[5]. McCauley JL, Killeen T, Gros DF, Brady KT, Back SE. Posttraumatic stress disorder and co-occurring substance use disorders: advances in assessment and treatment. Clin Psychol-Sci Pr 2012;19:283–304.

[6]. Hien DA, Wells EA, Jiang H, et al. Multisite randomized trial of behavioral interventions for women with co-occurring PTSD and substance use disorders. J Consult Clin Psychol 2009;77:607–19. [PubMed: 19634955]

[7]. Anglin MD, Hser Y-I, Grella CE. Drug addiction and treatment careers among clients in the Drug Abuse Treatment Outcome Study (DATOS). Psychol Addict Behav 1997; 11:308–23.

[8]. Walitzer KS, Dearing RL. Gender differences in alcohol and substance use relapse. Clin Psychol Rev 2006;26:128–48. [PubMed: 16412541]

[9]. Scott CK, Foss MA, Dennis ML. Pathways in the relapse—treatment—recovery cycle over 3 years. J Subst Abuse Treat 2005;28:S63–72. [PubMed: 15797640]

[10]. Witkiewitz K, van der Maas HLJ, Hufford MR, Marlatt GA. Nonnormality and divergence in posttreatment alcohol use: reexamining the Project MATCH data 'another way'. J Abnorm Psychol 2007;116:378–94. [PubMed: 17516769]

[11]. Muthen B, Shedden K. Finite mixture modeling with mixture outcomes using the EM algorithm. Biometrics 1999;55:463–9. [PubMed: 11318201]

[12]. Muthen B, Muthen LK. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. Alcohol Clin Exp Res 2000;24: 882–91. [PubMed: 10888079]

[13]. Xie H, Drake R, McHugo G. Are there distinctive trajectory groups in substance abuse remission over 10 years? An application of the group-based modeling approach. Adm Policy Ment Hlth 2006;33:423–32.

[14]. Hu MC, Griesler PC, Schaffran C, Wall MM, Kandel DB. Trajectories of criteria of nicotine dependence from adolescence to early adulthood. Drug Alcohol Depend 2012; 125:283–9. [PubMed: 22513378]

[15]. Colder CR, Mehta P, Balanda K, et al. Identifying trajectories of adolescent smoking: an application of latent growth mixture modeling. Health Psychol 2001;20:127–35. [PubMed: 11315730]

[16]. Hill KG, White HR, Chung IJ, Hawkins JD, Catalano RF. Early adult outcomes of adolescent binge drinking: person-and variable-centered analyses of binge drinking trajectories. Alcohol Clin Exp Res 2000;24:892–901. [PubMed: 10888080]

[17]. Hien DA, Morgan-Lopez AA, Campbell AN, et al. Attendance and substance use outcomes for the Seeking Safety program: sometimes less is more. J Consult Clin Psychol 2012;80:29–42. [PubMed: 22182262]

[18]. Najavits LM. Seeking safety: A treatment manual for PTSD and substance abuse. New York: Guilford Press, 2002.

[19]. Robins LN, Wing J, Wittchen HU, et al. The Composite International Diagnostic Interview. An epidemiologic Instrument suitable for use in conjunction with different diagnostic systems and in different cultures. Arch Gen Psychiat 1988;45:1069–77. [PubMed: 2848472]

[20]. Cacciola JS, Alterman AI, McLellan AT, Lin Y-T, Lynch KG. Initial evidence for the reliability and validity of a 'Lite' version of the Addiction Severity Index. Drug Alcohol Depend 2007;87:297–302. [PubMed: 17045423]

[21]. Blake DD, Weathers FW, Nagy LM, et al. The development of a Clinician-Administered PTSD Scale. J Trauma Stress 1995;8:75–90. [PubMed: 7712061]

[22]. Weathers FW, Keane TM, Davidson JRT. Clinician-administered PTSD scale: a review of the first ten years of research. Depress Anxiety 2001;13:132–56. [PubMed: 11387733]

[23]. Muthen LK, Muthen B. Mplus user's guide, 6th edn Los Angeles: Muthen & Muthen, 2009.

[24]. Hipp JR, Bauer DJ. Local solutions in the estimation of growth mixture models. Psychol Methods 2006;11:36–53. [PubMed: 16594766]

[25]. Brown EC, Catalano RF, Fleming CB, Haggerty KP, Abbott RD. Adolescent substance use outcomes in the Raising Healthy Children project: a two-part latent growth curve analysis. J Consult Clin Psychol 2005;73:699–710. [PubMed: 16173857]

[26]. Schwarz G Estimating the dimension of a model. Ann Statist 1978;6:461–4.

[27]. Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. Biometrika 2001;88:767–78.

[28]. Ramaswamy V, Desarbo WS, Reibstein DJ, Robinson WT. An empirical pooling approach for estimating marketing mix elasticities with PIMS data. Market Sci 1993;12:103–24.

[29]. Dennis ML, Scott CK, Funk R, Foss MA. The duration and correlates of addiction and treatment careers. J Subst Abuse Treat 2005;28:S51–62. [PubMed: 15797639]

[30]. Hser YI, Joshi V, Anglin MD, Fletcher B. Predicting posttreatment cocaine abstinence for first-time admissions and treatment repeaters. Am J Public Health 1999;89:666–71. [PubMed: 10224976]

[31]. Ouimette P, Moos R, Finney J. PTSD treatment and 5-year remission among patients with substance use and posttraumatic stress disorders. J Consult Clin Psych 2003;71:410–14.

[32]. Muthen BO, Asparouhov T. Wald test of mean equality for potential latent class predictors in mixture modeling, 2010 Available at: http://www.statmodel.com/download/meantest2.pdf (accessed April 2012).

[33]. Wang CP, Brown CH, Bandeen-Roche K. Residual diagnostic for growth mixture models: examining the impact of a preventive intervention on multiple trajectories of aggressive behavior. J Am Stat Assoc 2005;100:1054–76.

[34]. Witkiewitz K, Masyn KE. Drinking trajectories following an initial lapse. Psychol Addict Behav 2008;22:157–67. [PubMed: 18540713]

[35]. Muthen B Second-generation structural equation modeling with a combination of categorical and continuous latent variables: new opportunities for latent class—latent growth modeling In: Collins LM, Sayer AG, eds. New methods for the analysis of change. Washington, DC: American Psychological Association, 2001:291–322.

[36]. Chung T, Maisto SA, Cornelius JR, Martin CS, Jackson KM. Joint trajectory analysis of treated adolescents' alcohol use and symptoms over 1 year. Addict Behav 2005;30: 1690–701. [PubMed: 16098681]

[37]. Jackson KM, Sher KJ, Schulenberg JE. Conjoint developmental trajectories of young adult substance use. Alcohol Clin Exp Res 2008;32:723–37. [PubMed: 18331376]

[38]. Gueorguieva R, Wu R, Donovan D, et al. Naltrexone and combined behavioral intervention effects on trajectories of drinking in the COMBINE study. Drug Alcohol Depend 2010;107:221–9. [PubMed: 19969427]

[39]. McLellan AT. Have we evaluated addiction treatment correctly? Implications from a chronic care perspective. Addiction 2002;97:249–52. [PubMed: 11964098]

[40]. McLellan AT, McKay JR, Forman R, Cacciola J, Kemp J. Reconsidering the evaluation of addiction treatment: from retrospective follow-up to concurrent recovery monitoring. Addiction 2005;100:447–58. [PubMed: 15784059]

[41]. Laudet AB. The road to recovery: where are we going and how do we get there? Empirically driven conclusions and future directions for service development and research. Subst Use Misuse 2008;43:2001–20. [PubMed: 19016176]

[42]. Scott CK, Dennis ML. Results from two randomized clinical trials evaluating the impact of quarterly recovery management checkups with adult chronic substance users. Addiction 2009;104:959–71. [PubMed: 19344441]

[43]. Hser YI, Anglin MD, Grella C, Longshore D, Prendergast ML. Drug treatment careers. A conceptual framework and existing research findings. J Subst Abuse Treat 1997;14: 543–58. [PubMed: 9437626]

[44]. Foa EB, Keane TM, Friedman MJ. Guidelines for treatment of PTSD. J Trauma Stress 2000;13:539–88. [PubMed: 11109232]

[45]. Jacobsen LK, Southwick SM, Kosten TR. Substance use disorders in patients with posttraumatic stress disorder: a review of the literature. Am J Psychiat 2001;158:1184–90. [PubMed: 11481147]

[46]. Hien DA, Cohen LR, Miele GM, Litt LC, Capstick C. Promising treatments for women with comorbid PTSD and substance use disorders. Am J Psychiat 2004;161:1426–32. [PubMed: 15285969]

[47]. Hien DA, Jiang H, Campbell ANC, et al. Do treatment improvements in PTSD severity affect substance use outcomes? A secondary analysis from a randomized clinical trial in NIDA's Clinical Trials Network. Am J Psychiat 2010;167:95–101. [PubMed: 19917596]

[48]. Najavits LM, Runkel R, Neuner C, et al. Rates and symptoms of PTSD among cocaine-dependent patients. J Stud Alcohol 2003;64:601–6. [PubMed: 14572180]

[49]. Marlatt GA, Gordon JR, eds. Relapse prevention: maintenance strategies in the treatment of addictive behaviors. New York: Guilford Press, 1985.

[50]. May C, Foxcroft D. Minimizing bias in self-reports of health beliefs and behaviours. Health Educ Res 1995; 10:107–12. [PubMed: 10172341]

[51]. Ferguson SG, Shiffman S. Using the methods of ecological momentary assessment in substance dependence research—smoking cessation as a case study. Subst Use Misuse 2011;46:87–95. [PubMed: 21190409]

[52]. Chung T, Maisto SA, Cornelius JR, Martin CS. Adolescents' alcohol and drug use trajectories in the year following treatment. J Stud Alcohol 2004;65:105–14. [PubMed: 15000509]

[53]. Jacob T, Bucholz KK, Sartor CE, Howell DN, Wood PK. Drinking trajectories from adolescence to the mid-forties among alcohol dependent males. J Stud Alcohol 2005; 66:745–55. [PubMed: 16459936]

[54]. Schulenberg J, O'Malley PM, Bachman JG, Wadsworth KN, Johnston LD. Getting drunk and growing up: trajectories of frequent binge drinking during the transition to young adulthood. J Stud Alcohol 1996;57:289–304. [PubMed: 8709588]

[55]. Wiesner M, Weichold K, Silbereisen RK. Trajectories of alcohol use among adolescent boys and girls: identification, validation, and sociodemographic characteristics. Psychol Addict Behav 2007;21:62–75. [PubMed: 17385956]

[56]. Sher KJ, Jackson KM, Steinley D. Alcohol use trajectories and the ubiquitous cat's cradle: cause for concern? J Abnorm Psychol 2011;120:322–35. [PubMed: 21319874]

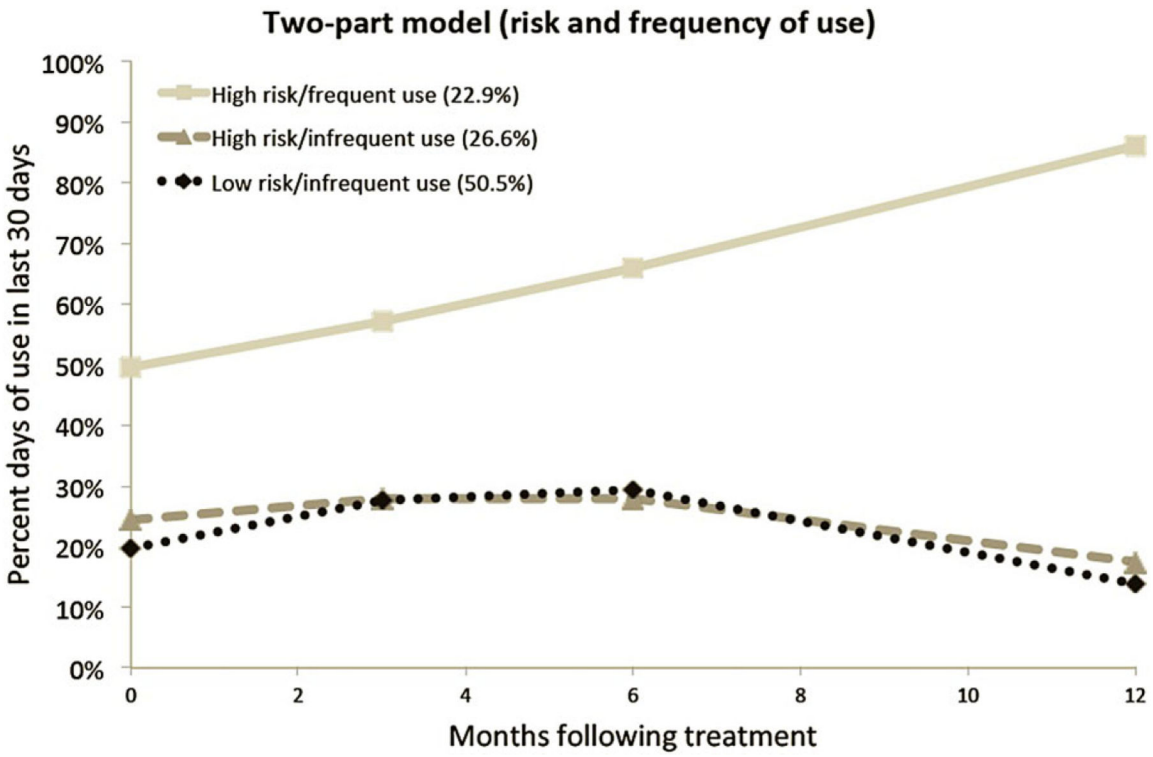

Figure 1.
Estimated means of two-part, three-class growth mixture model for 30-day frequency of substance use in the 12 months following treatment.

Table 1.

Baseline participant and diagnostic characteristics by treatment group for the intention-to-treat sample (n = 353)

Variable	Total	Seeking Safety (*n* = 176)[a]	Women's Health Education (*n* = 177)[a]
Age[b]	39.2 (9.3)	39.3 (9.5)	39.0 (9.1)
Race/ethnicity[b]			
African American/Black	34.0	33.0	35.0
Caucasian	45.6	47.16	44.1
Latina	6.5	3.98	9.0
Multiracial	13.3	15.34	11.3
Other	0.6	0.6	0.6
Marital status			
Married	17.6	14.8	20.3
Single	36.8	37.5	36.2
Divorced/separated	45.6	47.7	43.5
Years of education[b]	12.5 (2.4)	12.7 (2.3)	12.4 (2.6)
Employment			
Employed	40.2	40.3	40.1
Unemployed	55.0	54.6	55.4
Student/retired/disabled	4.8	5.1	4.5
Prior alcohol/drug treatment episodes	5.0 (7.9)	5.1 (7.4)	5.0 (8.2)
Controlled environment (past 30 days)	25.6	28.2	23.0
Currently prescribed psychotropic medication[c,d]	44.8	45.5	44.1
Baseline substance dependence diagnosis			
Cocaine	70.5	72.7	68.2
Stimulants	7.7	8.5	6.8
Opiates	25.6	25.6	25.6
Marijuana	27.2	27.8	26.6
Alcohol	56.1	59.7	52.5
More than one baseline substance dependence diagnosis[d]	29.5	33.5	25.4

Variable	Total	Seeking Safety (*n* = 176)[a]	Women's Health Education (*n* = 177)[a]
Baseline 7-day abstinence rate	46.2	44.1	46.9
PTSD diagnosis (% full)	80.4	76.7	84.2
CAPS severity, total	62.9 (19.4)	61.6 (19.36)	64.2 (19.4)
Lifetime traumatic experiences			
Child physical abuse	58.7	61.1	56.3
Adult physical abuse	84.8	83.4	86.2
Child sexual abuse	70.1	73.6	66.7
Adult sexual abuse	67.6	65.1	70.1
Transportation accident	72.7	72.2	73.3
Life-threatening illness	39.8	41.5	38.1
Exposed to violent death	19.3	16.5	22.2

Values are either means (with standard deviations) or percentages.

[a]There were no statistical differences between treatment groups on any variable.

[b]The variables were used as covariates in the models.

[c]Psychotropic medication was defined as medication prescribed for an emotional, psychological or psychiatric purpose to include depression, anxiety, psychosis, mood stabilisation or sleep disturbance.

[d]Variables included in randomisation stratification. CAPS, Clinician-Administered PTSD Scale; PTSD, post-traumatic stress disorder.

Table 2.

Model fit for unconditional and conditional growth mixture models

Model	BIC	Entropy	aLRT	*P*
Unconditional u-part				
1-class	1005.618	—	—	—
2-class	1010.697	0.737	190.784	<0.001
Unconditional y-part				
1-class	280.177	—	—	—
2-class	224.351	0.725	73.321	0.02
3-class	197.399	0.737	45.760	0.01
4-class	187.915	0.716	29.086	0.31
Unconditional two-part				
1-class	1479.227	—	—	—
2-class	1303.283	0.743	203.921	<0.001
3-class	1270.392	0.769	70.458	<0.001
Conditional two-part 3-class	1265.486	0.839	65.069	0.05

The best log likelihood was not replicated for three-class unconditional u-part and four-class unconditional two-part models. The results of these two models were not shown due to the generalisability of the model. aLRT, adjusted likelihood ratio test; BIC, Bayesian information criterion.

Table 3.

Distribution of covariate means and equality tests of means across latent trajectory classes of primary substance use using posterior probability-based multiple imputations in three-class LGMM (n = 288)

	Trajectory classes							
	Low risk/infrequent use *n* = 145		High risk/infrequent use *n* = 77		High risk/frequent use *n* = 66		Wald test of mean equality	
Covariates	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	χ^2	***P* value**
Age	37.15	0.78	41.89	1.15	38.64	1.28	10.670	0.005
PTSD severity, baseline	60.741	1.79	61.98	2.42	65.84	2.53	2.429	0.297
Prior psychiatric treatment episodes	2.72	0.35	3.43	1.04	3.23	0.88	0.711	0.701
Percentage of using days in 30 days prior to study	16.20	2.50	35.90	4.60	46.30	5.60	37.975	0.000
Total lifetime years of alcohol/drug use	10.43	0.67	13.04	1.07	12.14	1.22	5.325	0.070
Prior SUD treatment episodes	4.69	0.62	4.66	0.55	4.97	0.72	0.104	0.949
Treatment type (SS vs. WHE)	0.53	0.04	0.49	0.06	0.47	0.07	0.702	0.704
Treatment attendance	7.38	0.37	6.65	0.52	6.51	0.54	2.581	0.275
Change in PTSD severity from baseline to 1-week follow up	−31.95	1.83	−24.56	2.32	−25.41	2.76	8.890	0.012
Psychiatric treatments during 1-year follow-up period	0.74	0.28	0.54	0.19	0.19	0.06	4.269	0.118
SUD treatment episodes during 1-year follow-up period	1.00	0.07	0.70	0.09	0.73	0.10	9.171	0.010

LGMM, latent growth mixture modelling; PTSD, post-traumatic stress disorder; SE, standard error; SS, Seeking Safety; SUD, substance use disorder; WHE, Women's Health Education.

Table 4.

Adjusted odds ratios for comparison between three trajectories (n = 266[a])

Covariate	Low risk/infrequent use versus high risk/infrequent use reference group AOR (CI 95%)	High risk/frequent use versus high risk/infrequent use reference group AOR (CI 95%)	High risk/frequent use versus low risk/infrequent use reference group AOR (CI 95%)
Treatment type (SS vs. WHE)	1.76 (0.74–4.21)	1.36 (0.43–4.29)	0.77 (0.32–1.84)
Age	0.91 (0.87–0.95) **	0.89 (0.84–0.95) **	0.99 (0.93–1.04)
Prior SUD treatment episodes	1.00 (0.97–1.04)	0.99 (0.93–1.05)	0.99 (0.93–1.04)
Percentage of using days in 30 days prior to study	0.07 (0.02–0.21) **	1.44 (0.42–4.98)	20.88 (5.51–79.19) **
Treatment attendance	1.04 (0.94–1.15)	0.99 (0.89–1.10)	0.95 (0.86–1.04)
Change in PTSD severity from baseline to 1-week follow up	0.97 (0.95–0.99) **	0.99 (0.97–1.02)	1.02 (1.00–1.05) †
SUD treatment episodes during 1-year follow-up period	1.86 (1.12–3.10) *	1.02 (0.49–2.14)	0.55 (0.29–1.02) †

* $P < 0.05$;

** $P < 0.01$;

† $P < 0.10$.

Treatment type coded as: Seeking Safety = 1,Women's Health Education = 0.

[a]Excludes 22 cases with missing data.

AOR, adjusted odds ratio; CI, confidence interval; PTSD, post-traumatic stress disorder; SS, Seeking Safety; SUD, substance use disorder; WHE, Women's Health Education.