7-26-2018

Operationalizing Recovery from Substance Use Disorders among Adolescents in High School

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Abstract

The term “recovery” has been widely adopted in substance use-related literature. But no operational standard can be found regarding how to measure recovery among substance use population under 18 years old. Using data from 294 adolescents who were followed for 12 months after receiving treatment for substance use disorders (SUDs), we find converging evidence of a general recovery factor *v*, extracted from 15 indicators, that potentially reflects adolescents’ level of recovery from SUDs. The latent *v* score generated using factor loadings is associated with criterion variables in the expected directions where positive correlations were found with for life satisfaction, social support, and enrollment in recovery high school (RHS), and negative correlations with peers’ supporting attitudes toward substance use. A significant interaction was found between RHS enrollment and time on the latent *v* score. Three sub-types of recovery – struggled recovery, inconsistent recovery, and consistent recovery – were identified based on differential distributions of the indicators. Most people were in the struggled recovery status at baseline, but a higher proportion of RHS students transitioned into inconsistent and consistent recovery statuses over time.

Key words: recovery, substance use, high school, adolescents, operationalization

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among Adolescents in High School

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

[2018]

APPROVAL PAGE

Doctor of Philosophy Dissertation

Operationalizing Recovery from Substance Use Disorders

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Acknowledgments

Thanks to the committee members (Dr. Blair T. Johnson, Dr. Kun Chen, and Dr. Rhiannon Smith) for their continuous support throughout the study. Thanks to Dr. Felicia Pratto, and Dr. Nairan Ramirez-Esparza for serving as the readers for the study. Last but not least, thanks to Dr. Andrew Finch and Dr. Emily Alden Hennessy for making this study possible in the first place and for helping me to reach an agreement to obtain the data.

The work to create the original database was supported by Grant Number R01DA029785from the National Institute on Drug Abuse to Dr. Andrew Finch. The project also benefited from the Clinical and Translational Science Award (CTSA) program, through the NIH National Center for Advancing Translational Sciences (NCATS) grant UL1TR000427.

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Introduction

Rationale and Goals

Recovery from substance use disorders (SUDs) is a concept that has been widely discussed in the field of substance use research. According to the National Survey on Drug Use and Health, about 21.5 million Americans ages 12 and older (8.1%) were classified with a SUD in 2014. In 2015, approximately 1.3 million adolescents (5.1 percent of this age group), 5.4 million young adults (15.5 percent of this age group), and 15.0 million adults aged 26 or older (7.2 percent of this age group) needed substance use treatment. For SUD treatments, recovery is a central factor to be considered. As this concept become increasingly embraced by health care policy – as part of the Affordable Care Act to support continuing care for chronic illness (45 CFR part 156) – it is becoming even more pressing to develop a measure for recovery so that the level of recovery can be quantified and evaluated empirically.

The importance of recovery has been discussed in verbal and theoretical frameworks (Marton, 2016), but a validated measure has not yet been established. Over the past decade, researchers made considerable progress in defining recovery from an experiential perspective (Dodge, Krantz, & Kenny, 2010; Kaskutas et al., 2014; Marton, 2016), but operationalization of recovery – defining recovery in a measurable factor – is still in its early stage. Very few studies have attempted to operationalize recovery using empirical data, even rarer is the effort dedicated to recovery operationalization among adolescents aged 12 to 17, whose developmental needs often require SUD treatment and evaluation standards that are different from those designed for adults (Morrison, 1990). The goal of the research reported here was to test the hypothesis that recovery among adolescents, like that among adults, can be realized through its measurable equivalence.

The formation of a recovery measure may improve the efficiency and accuracy of treatment evaluation among adolescents with SUDs.

Literature Review

Although still a developing concept, recovery from SUD, in the grand scheme of things, is not different from the general definition of recovery: a return to a normal state of health, mind, or strength. Many definitions have been proposed over the years under this scheme. SAMHSA, for example, defines recovery as a process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential (SAMHSA, 2012). Galanter on the other hand, defines recovery as experiences not directly observable, but are self-reported through the personal interpretations from the substance-using individuals (Galanter, 2007). Both definitions imply recovery as a latent construct or procedure. Given that these conceptual definitions are not quantifiable, people have also proposed different working definitions of recovery for application purpose. Among the many early attempts to quantify recovery, sobriety (i.e., abstinence from alcohol and other non-prescribed drugs) was the most popular measure (Laudet, 2007; Steindler, 1998). In the recent decade, however, a broader definition of recovery is gaining recognition, one that puts the focus on improved overall life quality and accepts that recovery occurs across a spectrum via many pathways (Laudet, 2007; W. L. White, 2007). The Substance Abuse and Mental Health Services Administration (SAMHSA), in its 2012 report, defined recovery as “a process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential” (SAMHSA, 2012). Although sobriety is seen as a necessary condition for early recovery, it is now considered inappropriate to be used as a stand-alone indicator for recovery (Hennessy, Glaude, & Finch, 2017).

In recent years, researchers have largely updated the working definition of recovery, by incorporating various aspects that are deemed relevant to the concept. The Betty Ford Consensus Panel defines recovery by three parts: sobriety, personal health, and citizenship, though the inclusion of citizenship is controversial (Betty Ford Consensus Panel, 2007). McLellan and colleagues also proposed “recovery” as a three-domain concept including substance use, employment/self-support, and criminal activity. Some researchers have chosen to define recovery as a process through which people utilize resources to resolve their substance use problems (McLellan, Chalk, & Bartlett, 2007). This process-oriented perspective typically put much emphasis on supportive resources for recovery, such as living environment, physical and emotional health, and family relationship, etc. (W. White, 2008). SAMHSA’s working definition of recovery, for example, encapsulates resources in four different dimensions: home (stable and safe housing), community (social networks), purpose (employment and education), and health (abstaining from substance, physical and emotional well-being) (SAMHSA, 2012).

In contrast to the considerable effort that has been put into defining recovery, fewer attempts have been made to operationalize it. Among the available literature, we identified three studies that can pave the way for the current one. Dodge and colleagues, after interviewing professionals in SUD, generated a model with 7 components: physical, biomarker, psychological, psychiatric, chemical dependency, family/social, and spiritual (Dodge et al., 2010). The model is hypothetical, but each domain is operationally defined by valid instruments, and as such the model can be validated by confirmatory factor analysis. Kaskutas and colleagues on the other hand, validated their 35-item measure among adults who self-identified as being in recovery or recovered, and proposed a four-factor structure: the three-item “abstinence in recovery”, the 15-item “essentials of recovery” (e.g., enjoy life without drinking, etc.), the 10-item “enriched recovery” (e.g., developing inner strength, etc.), and the seven-item “spirituality of recovery” (e.g., being grateful, etc.) (Kaskutas et al., 2014). Finally, Garner et al. proposed a smaller model with 5 components (physical health, medical health, sobriety, satisfaction with relationship, and daily function) based on surveys with adults at 15 years’ post-intake (Garner, Scott, Dennis, & Funk, 2014). This is the first time that a study reveals the plausibility of using 5 different variables to generate a single latent recovery factor, which was then used to predict health-related quality of life.

The Current Study

By analogy with Garner’s study, we define recovery as a latent construct, *v,* that can be inferred from observable variables in multiple dimensions. Here recovery is a property itself, not just the individual items from which it is inferred. Unlike previous work that examined recovery among general adult population, one of our goals is to determine whether a recovery measure can be formulated for adolescents. The measure should have enough breadth to cover essential aspects of recovery, while also maintains its own scope to be manageable and practically useful. To better tailor the measure to adolescents, we also took inspiration from a previous study on adolescent’s recovery capital, in which the researchers categorized recovery resources into human capital (e.g., cognitive health, school grades, problem-solving skills etc.), financial capital (e.g., stable living, caregivers’ income, etc.), social capital (e.g., supportive friends and family, youth-parent relationship, etc.) and community capital (e.g., perceptions of substance use norms, recovery schools, etc.) (Hennessy, 2017). In order to align the scope of the measure to its function as a measure for adolescents, we will only incorporate resources that are in direct possession of adolescents, instead of those belong to parents or community. Resources owned by peers, family, and community may be predictors for recovery, but are not understood as innate elements of recovery.

The concept of recovery has been used as a theoretical foundation for adolescents' SUD treatments. Nevertheless, the evaluation of treatments often dodges the question of what recovery actually is. One of the previous studies evaluated the effect of recovery high school (RHS) – schools designed specifically for students in recovery from SUDs – on supporting recovery, but in the absence of an established measure for recovery, the researchers instead used frequency of substance use and academic performance as standards of evaluation (Finch, Tanner-Smith, Hennessy, & Moberg, 2018). Some researchers used the 12-item Recovery Environment Risk Index (RERI) designed to assess the number of environmental risk factors (e.g., homelessness, living with substance use, violence and abusiveness) as an alternative measure for recovery (Garner, 2014). Some others used the Recovery Assessment Scale designed for mental health patients among substance–abusing youth. The scale contains four factors: "personal determination" (i.e., I have a desire to succeed, etc.); "skills for recovery" (i.e., I am willing to ask for help; etc.), "self-control in recovery" (i.e., I can handle stress, etc.); and, "social support and moving beyond recovery" (i.e., It is important to have fun, etc.), which apparently lacks specificity for substance use problems (Gonzales, Hernandez, Douglas, & Yu, 2015). Due to the shortage of prior standards for comparison, we opt to verify the external validity of our recovery measure by examining its association with a list of criterion variables. A criterion variable is selected if there is prior evidence or theoretical underpinning to postulate an association between the variable and recovery. To better understand the meaning of our tentative recovery measure, we will further enrich the findings by proposing potential sub-types of recovery based on frequency profile of the indicators behind recovery, and examining how likely people are transitioning between each sub-type during the follow-ups.

Hypotheses

As one of the earliest attempts to operationalize recovery among adolescents, we assume that there is a single factor v that functions as a measure for recovery. We chose letter v instead of r to represent the recovery factor because the latter is more commonly known as the correlation coefficient. This factor, if exists, should be associated with criterion variables in the expected directions. Based on evidence in our previous studies, RHS student should score higher on recovery than non-RHS students. Moreover, we assume that indicators for v will allow us to detect sub-types of recovery, the prevalence of which will distribute differently between RHS and non-RHS students.

Method

Overview of RHS Quasi-Experiment

Data were collected through a longitudinal quasi-experiment to test effectiveness of recovery high schools (RHSs) as continuing care. Details of the study are described elsewhere (Finch et al., 2018; Hennessy, 2017). Briefly, adolescents discharged from the substance use disorder (SUD) treatment program were recruited into the study. Measures were taken at baseline, 6 months and 12 months. After adjusting for propensity score (i.e., predicted probability of attending an RHS), adolescents attending RHS were more likely to report being abstinent from using substances at the

6-month follow-up (*OR* = 4.36, p = .026) and less likely to be absent from school (d = -0.56, p =.028). No difference was found in days of substance use or school grades.

Participants

In total, 294 participants were recruited from 10 SUD treatment facilities in Minnesota, Wisconsin, and Texas. About half (n = 148) were enrolled in RHS at baseline (Table 1). A participant must be enrolled in an RHS during the past 28 days at the time of each survey to be categorized as an RHS student. This definition was determined by the research team after consulting with RHS staff members with extensive experience helping adolescents with SUDs. Participants who dropped out of RHS at the follow-ups did not differ from those who stayed at RHS on variables of interest (i.e., variables reported in Table 1; *p*s > .05 for *t*-tests and ANOVA, tests not shown). The participants tended to be between 15 and 18 years of age and were primarily White (between 77% and 86%).

Measures

Except for demographic information, which was collected at baseline only, all measures used in the study were collected at baseline, 6 months and 12 months. The possible range of each measure appears in Table 1.

Primary Measures of Recovery

The following measures are used in the main analysis as indicators for recovery. We also converted them into binary indicators for latent transition analysis (see analysis). The measures were typically dichotomized at the medians if not specified otherwise.

Frequency of substance use is measured by days of use in the past 90 days. We measured alcohol, marijuana (mj), and drugs other than alcohol/mj separately using the Timeline Followback method (Sobell, Brown, Leo, & Sobell, 1996). We also dichotomized the measures into complete abstinence (0 day) vs non-abstinence (≥1 day) for latent transition analysis.

Grade point average (GPA) was used as a surrogate measure of cognition due to the lack of direct measures of cognitive function in the dataset. GPA has proven capacity to capture cognitive skills (Heckman, 2008). Adolescents were asked to report the typical grades they received in the past 3 months in reading and mathematics (range: 0 [mostly Fs] to 4 [mostly As]). Grades were also dichotomized into GPA ≥ 3.0 vs GPA < 3.0 for latent transition analysis.

Substance use disorder (no disorder = 0, abuse = 1, dependence = 2) was diagnosed using MINI Structured Clinical Interview (MINI-SCID) consisting of 11 criteria (Sheehan et al., 1999). Dependence was diagnosed when three or more dependence criteria were met. Among those with no dependence diagnosis, abuse was diagnosed when at least one abuse criterion was met. For latent transition analysis, we merged the abuse and the dependence into one single category. Alcohol use disorder and drug (other than marijuana) use disorder were measured separately.

Antisocial personality disorder was defined as having two or more symptoms using the 6 criteria for antisocial personality from the MINI-SCID (Sheehan et al., 1999). This measure is binary coded (no disorder = 0).

Neighborhood social connection was measured by 6 items (α = 0.78) adapted from the Profiles of Student Life Attitudes and Beliefs (Leffert et al., 1998; Zaff, Boyd, Li, Lerner, & Lerner, 2010). Responses range from 1 (strongly disagree) to 5 (strongly agree). The final measure was generated by taking the mean score of each participant's responses.

Youth-parent relationship was measured using the mean score of responses to 11 items (Cronbach's α = 0.86) from the Youth Happiness with Parent Scale (DeCato, Donohue, Azrin, &

Teichner, 2001). Responses range from 0% (completely unhappy with parents in this area) to 100% (completely happy with parents in this area).

Crime and violence was measured by counting the number of problems reported in the Global Appraisal of Individual Needs Q3 - Crime & Violence Screener (Dennis, 2010). The screener includes 5 common crime and violent behaviors, including pushing people, stealing things, distributing illegal drugs, alcohol-impaired-driving, and damaging others' property.

Personal consequence of substance use was measured by the Personal Experience Inventory (PEI) (Winters & Henly, 1989). Our scale includes 4 of the 11 items on the original scale regarding things people have done to get drugs/alcohol (i.e., stole and sold things, done people favors, sell personal belongings, and done illegal things). Responses range from 1 (never) to 4 (often). The final measure was the summative score of the responses.

Substance use expectancy was measured using summative score of responses to corresponding items from the PEI (Winters & Henly, 1989). The psychological benefits were measured by 5 items ($\alpha = 0.72$) and social benefits were measured by 9 items ($\alpha = 0.77$). We asked participants how much they agreed with each of the stated benefit (e.g., feel less shy and make friends, feel less tense or uptight, etc.). Responses range from 1 (strongly disagree) to 4 (strongly agree).

Positive problem orientation and *rational problem solving* are two factor scores extracted from the 25-item Social Problem Solving Inventory-Revised (D'Zurilla, Nezu, & Maydeu-Olivares, 2002). Example items related to the two factors include seeing a problem as an opportunity for learning, not giving up on a problem that can't be solved initially, getting as many facts as possible when facing a problem to be solved, etc.

Criterion Variables

The following variables were used as criterion variables to examine their associations with the latent recovery factor. RHS enrollment status is a dummy-coded variable (enrolled = 1, not enrolled = 0). A participant's enrollment status is based on whether he/she attended an RHS during the past 28 days by the time of each survey at baseline, 6 months, or 12 months. Peer attitude/preference toward substance use was measured by the average response to 13 related items in the PEI (e.g., most friends think it's ok to use substance, close friends think substance use is a good way to pass time, etc.; $\alpha = 0.87$) (Winters & Henly, 1989). The higher the score, the more favorable peers' attitudes are toward substance use. Life satisfaction was measured by the average response to 6 items ($\alpha = 0.69$) adapted from the Life Satisfaction Index in the Global Appraisal of Individual Needs (GAIN) (Dennis, 2010). A higher score indicates a higher life satisfaction. Social support was measured by counting the types of social support (e.g., friends, family, health providers, etc.) one received during the past 3 months, using the 9-item General Social Support Index in the GAIN (Dennis, 2010).

Analysis

Factor Analysis

The primary question we examined was whether a recovery model could be established. Is there a single factor, v, that incorporates the multidimensional aspects of recovery? To answer this question, we first used exploratory factor analysis (EFA) to determine the latent structure of the observed variables, and then extracted a single latent factor from a low-dimensional latent variable space. A visualization of the conceptual model appears in Figure 1. Circles represent latent variables and rectangles represent measured variables. The initial EFA consisted of 30 items, selected based on suggestions from previous literature (see Introduction). Both the scree plot and parallel test suggested a 6-factor solution. After performing principal axis extraction with varimax rotation, items with loadings lower than 0.4 were eliminated, which reduced the number of items to 15. Two items – positive problem orientation and rational problem solving – were latent constructs from a verified scale. To ensure theoretical integrity, we allocated an extra latent variable to accommodate them. We then performed a second-order confirmatory factor analysis (CFA) to validate the proposed model. We started by assuming all variables would independently load onto their corresponding latent variables. Correlations were then allowed between items to improve model fit. Parameters were estimated using pseudo-maximum likelihood procedure and estimates were aggregated over time (R lavaan.survey package, version 1.1.3.1). Robust standard errors were calculated by allowing heteroscedasticity across individuals. All derived fit indices and statistics were adjusted for within-subject clustering through the Satorra-Bentler scaling correction (Satorra & Bentler, 2010).

Missing data ranged from 1% to 50% across the variables in this study (Table 1). The Little test (R. J. A. Little, 1988) indicated that data were not missing completely at random (p<0.001). Chi-square tests for independence revealed that proportions of missing values in selected items are higher among non-RHS students. To impute missing values, we attempted several imputation approaches, including multiple imputation by chained equations (MICE), k-nearest neighbor imputation, soft-impute by iterative soft thresholding of SVD decompositions, and matrix completion by iterative low-rank SVD decomposition (mice R package, version 3.0.0, fancyimpute

Python package, version 0.3.1). The data are assumed to be missing at random[1]. Analyses with and without imputation produced similar path coefficients, but model fit was much improved with imputation. Different imputation methods yielded consistent results. We chose to present path coefficients generated from data imputed using MICE because it's a more common approach in the literature. Typically 40 datasets are recommended for data with missingness up to 50% (J. E. Graham, Allison, & Tamika, 2007). We thus imputed 40 copies and the results were combined using Rubin's equations (Rubin, 1987).

To further verify the validity of the recovery model, we calculated a *v* score (latent recovery score) using factor loadings and assessed its association with multiple criterion variables (i.e., enrollment status, peer attitude, etc.) through regression analysis. We used generalized estimating equation (GEE) with exchangeable correlation structure to account for correlation of data within individuals. The analysis also helps to test the fundamental hypothesis that RHSs promote better recovery than regular high schools.

Latent Transition Analysis

Latent transition analysis (LTA) is an extension of the latent class analysis (LCA), a type of finite mixture model that identifies unobservable groups within a population. The LCA can be used to represent multidimensional latent variables by reducing a large number of categorical variables to a few subgroups (Lanza & Collins, 2008). The LTA extends the function of LCA to longitudinal data and is an excellent way of modeling changes over time (J. W. Graham, Collins, Wugalter, Chung, & Hansen, 1991). We used LTA to offer a more enriched account of the *v* factor proposed in

[1] Missing at random (MAR) means the propensity of missing is related to observed data only. In this study for example, we assumed that conditional on RHS enrollment, missingness is independent of missing values (R. Little, 2002).

the SEM (PROC LTA, SAS package, version 1.3.2). Models with two, three, four, and five latent statuses were compared to identify the optimal number of statuses. Values for the likelihood-ratio G^2 statistic, degrees of freedom, Akaike's information criterion (AIC) and Bayesian information criterion (BIC) appear in Table 3. Based on the table, a three- or four-status model appears to represent the data best. An examination of the interpretation of the latent statuses revealed that the more parsimonious three-status model was preferred. The item-response probabilities for each response category were constrained to be equal across time.[2] Parameters were estimated by maximum likelihood using the Expectation-Maximization (EM) algorithm.

Due to the discrete nature of the variables in LTA, missing values were handled using random forest algorithms (missForest R package, version 1.4). This approach has the desirable properties to handle mixed-type data including complex interactions, and shows reliable performance under moderate to high missingness (Tang & Ishwaran, 2017). Imputation (number of trees = 300) produced results largely comparable to those from the data without imputation. Yet, a saturated model was non-estimable in the original dataset, due to missingness.

[2] Although the G^2 difference between time-constrained and non-constrained model was statistically significant, a careful inspection of the item-response probabilities suggested that the interpretation of the three latent classes was very consistent over time. Therefore, the more parsimonious model was chosen.

Results

Table 1 presents the descriptive statistics for each variable at baseline, 6, and 12 months. On average, there is a declining trend in days of substance use, number of violent behaviors, and diagnosis of SUDs and antisocial personality. An increasing trend can also be spotted in youth-parent relationship, social connection, GPA and life satisfaction.

Results of factor analysis (Figure 1) revealed that recovery can be modeled by a single second-order latent factor (*v*), which is loaded on by 7 first-order latent factors, accounting for 69% of variance in the 15 observed variables. Confirmatory factor analysis suggested excellent fit of the model with the data [$\chi^2 = 66.02$, $p = .08$, $df = 51.53$; CFI = .973, RMSEA = .032, SRMR = .034]. Factor loadings of the model are in the expected directions. Among the first-order latent factors, substance use expectancies, substance use frequency, substance use disorder, and general negativity have negative loadings, while cognition, general positivity and social problem-solving skills have positive loadings. Furthermore, correlations between *v* (latent recovery score) and criterion variables are in the expected directions. In particular, *v* is positively correlated with life satisfaction ($r = 0.29$, $p < .001$) social support ($r = .18$, $p < .001$), and enrollment in RHS ($r = .12$, $p < .001$), and negatively correlated with peers' preference toward substance use ($r = -.39$, $p < .001$). Yet we also found that the factors one might have expected to correlate with recovery – such as depression and a variety of other psychiatric disorders – did not.

Table 2 presents results of the regression analysis with *v* score as the outcome, and criterion variables that are significantly associated with it as the predictors. A significant interaction was found between time and RHS enrollment, indicating that *v* was more likely to increase over time among adolescents enrolled in RHS. Specifically, RHS students started with a lower *v* at baseline

(β = -.045, p = .007), but they surpassed their non-RHS counterparts at 6 (β = .129, p < .001), and 12 months (β = .121, p < .001). Meanwhile, non-RHS students showed a slight decline in v at 6 and 12 months (β = -.017, not significant (*ns*), and β = -.036, *ns*, respectively). This result is consistent with the hypothesis that RHS promotes better recovery. The interaction still holds after adjusting for other variables. Also, peer preference is negatively associated with v in the adjusted model, while life satisfaction and social support are positively associated with v. Figure 2 presents the interaction visually.

One way to understand the recovery factor v is to look at its latent factor score, where the higher the score the better the recovery. But in order to gain a deeper and more comprehensive understanding of its meaning, we examined LTA for a closer look at the variables that generate v. Each column of Table 4 shows, for a particular latent status, the item-response probabilities for each response category, the overall probability of status membership at each time, the transition probabilities given latent status membership at the previous time. We labeled the three latent statuses as “struggled recovery”, “inconsistent recovery”, and “consistent recovery” in view of the item-response probabilities. Compared to people in the other two statuses, a larger proportion of struggled recovery adolescents were diagnosed with drug use disorders (.92 vs .49 and .04, respectively) and alcohol use disorders (.58 vs .08 and .02). They are also more likely to report a higher number of personal consequences (.35 vs .00 and .03), perceive higher social benefits of substance use (.83 vs .62 and .67), being diagnosed with antisocial personality (.36 vs .02 and .04), having a lower level of positive oriented problem-solving skill (.57 vs .97 and .91), and being involved in more crime and violence (.55 vs .14 and .17) than people in the other two groups. The status of inconsistent recovery and the status of consistent recovery are similar in most aspects, but their main difference lies in the level of abstinence. Adolescents in the inconsistent recovery group, though with a low prevalence of alcohol use disorders, continue engaging in alcohol drinking during the past 90 days. In fact, this group boasts the highest prevalence of both alcohol and marijuana use among all three groups. In contrast, those with consistent recovery status not only have the lowest prevalence of alcohol and drug use disorders but also have the lowest rate of adoption of any substance use behaviors during the past 90 days.

Among the three statuses, the most common one at baseline is struggled recovery. However, the inconsistent and the consistent statuses become more prevalent at 6 and 12 months. The transition probabilities appear stable over time among the consistent recovery group, but rather polarized among struggled-recovery and inconsistent-recovery statuses. The consistent recovery status had about 50% of chance transitioning into other statuses at both 6 months and 12 months. In contrast, adolescents in the struggled recovery status and inconsistent recovery status started with very high probabilities (.75 and 1.00) of transitioning into other statuses at 6 months, but ended up with rather low probabilities (.19 and .03) of transitioning out of their current statuses at 12 months. RHS enrollment was added to the three-status model as a grouping variable to compare the prevalence of each latent status between RHS and non-RHS participants (Table 5). At baseline, participants were almost exclusively in the struggled recovery status with no difference by RHS enrollment. At follow-ups, a considerably larger proportion of RHS students moved to the inconsistent and consistent recovery status than the non-RHS students.

Discussion

The results of the current study provide evidence for the existence of a single latent recovery factor *v* among adolescents with SUDs, analogous to the similar finding among adults, but with slightly different components. Notably, this recovery factor appears to depend both on substance use and personal assets including family and social connection, perceptions and grades, personality and problem-solving skills. The association between recovery factor and its potential predictors (i.e., RHS enrollment, peers' attitude toward substance, etc.) are in the expected directions. Three sub-types – those with struggled recovery, inconsistent recovery and consistent recovery– were discovered based on a frequency profile of indicator variables.

Although these findings confirmed some of our hypotheses, they also raise many additional questions. In our study, the adverse elements of recovery (e.g., expected benefits of substance, violent behavior and personality, etc.) have larger factor loadings than positive elements (e.g., social connection and problem-solving skills, etc.). In the study by Garner et al., however, there seems to be a tie between the positive factors and the negative ones. Except for sobriety, which has the lowest loading (0.2) among all indicators of recovery, medical health problems and satisfaction with relationship have similar loadings (-0.58 and 0.4 respectively), and so do physical health problems and daily functioning (-0.74 and 0.75 respectively). Apparently, neither of the studies can provide a definitive answer regarding whether we should pay more attention to the supportive elements, or the obstructive ones. Why bad events seems stronger than good ones may be a philosophical question that is beyond the scope of the study (Baumeister, Bratslavsky, & Finkenauer, 2001), but given that certain elements may be easier to modify than others from a behavioral intervention perspective, our findings may raise a question regarding whether it would be more efficient for support services and interventions to focus on elements that have a stronger presence in recovery? In the face of dwindling resources in health care, future studies should provide a more compelling answer to this interesting question.

Consistent with the assumption that attendance in RHS sustains and reinforces the therapeutic benefits gained from SUD treatment (Finch, Moberg, & Krupp, 2014), our finding suggests that RHS students scored higher on recovery than non-RHS students during the follow-ups. Noticeably, RHS student started with a lower recovery score than non-RHS students at baseline. This finding agrees with the knowledge that RHS students typically have more risk factors for substance use and relapse than the comparison samples at both local and national level (Tanner-Smith, Finch, Hennessy, & Moberg, 2018). The fact that they caught up and surpassed non-RHS participants in recovery within 6 months, despite a lower starting point, makes the effect of RHS attendance even more impressive. The actual mechanism behind the success of RHS is still under investigation, but in general, school always plays a central role in substance use by providing adolescents with their first access to substance through social network (Cleveland & Wiebe, 2003; Piper, Moberg, & King, 2000). One study found that virtually all adolescents returning to their old school after treatment reported being offered drugs on their first day back in school (Spear & Skala, 1995). Indeed, failure to establish social contact with nonusers is an important reason for relapse among adolescents (Spear & Skala, 1995). In the current study, we do not have data on the prevalence of substance use in each school. But an interesting question left to be answered is whether improved recovery among students in RHS could be a result of departure from the original social network and reduction of accessible substance. Would it have similar effect on recovery by sending adolescents to a regular high school that has an extremely low prevalence of substance use?

We believe there is more to the success of RHS than changes of network and environment, but identification of the most critical success factors requires some initial guesses. Future researchers are welcomed to correct or expand our assumption.

Our previous discussion of social network in schools leads naturally to the next finding, where peers' approving attitudes toward substance use negatively predicted recovery in the study. It is a well-known fact that adolescents' substance use is always affected by their perception of peers' attitude toward substance use (Mason, Mennis, Linker, Bares, & Zaharakis, 2014). Our finding not only accentuates this fact, but also extends it by showing the influence of peer attitude on overall recovery. In fact, Mason et al. found that indifferent attitude toward substance use among close friends was enough to increase substance use (Mason et al., 2014). It thus comes as no surprise that having peers who approve of substance use would lead to increased substance use and reduced recovery over time. Substance approving peers has been listed as a component of social capital of recovery among adolescents (Hennessy, 2017). Yet, it is only one of the many aspects of instability in adolescents' social network. Substance use, like other risk behaviors, may be underpinned and sustained by the numerous exchanges of resources between individuals and their networks (Johnson et al., 2010). Therefore, we encourage researchers to seek out factors in an adolescent's social network that both have strong impacts on recovery, and are feasible to enhance or rectify through interventions. If these factors cannot be easily identified, then will it be possible to change the composition of an adolescent's social network completely? Perhaps transferring to a new school or moving to a new location is one approach, or perhaps teaching adolescents to selectively include people in their social network is another approach. This unresolved question is left to be tackled by future studies.

Although our study supports the existence of a recovery factor, we have not provided a standard to interpret the factor score (such as grouping the scores using cut-off points). We in fact never intended to do so given the very preliminary evidence. Instead of assigning meanings to arbitrarily grouped factor scores, we resorted to LTA to detect meaningful sub-types of recovery. This method may shed some light on how someone on the high or low end of recovery score actually looks, and how stable each sub-type is over time. The process of naming each sub-type is quite subjective, but the analysis per se suffices the purpose of distinguishing people who are doing well from those who are not doing well in recovery through measurable indicators. A problem with this analytical approach, however, is the potential inconsistency of the subtypes that could emerge in the literature due to the subjectivity in labeling categories. A similar problem has already been observed in the field of depression, where latent class analysis (the cross-sectional version of LTA) is often used to elucidate clinically relevant depression subtypes. After reviewing all available literature, (Ulbricht, Chrysanthopoulou, Levin, & Lapane, 2018) found that no consistent set of depression subtypes could be identified. Nevertheless, we believe that consistency in labels is not so important as compared to understanding the general pattern of indicators in actual clinical practices. Overlapping patterns will emerge once more researchers start to explore this topic. Clinicians can use their knowledge of the overlapping patterns of indicators to supplement their diagnoses of patients' recovery status.

In this study, psychiatric disorder was not a meaningful component in the recovery measure. It shared a non-significant loading when being included in the measure, and substantially reduced the overall model fit in CFA. We also did not find the various psychiatric disorders (e.g. depression, psychotic disorders, etc.) to be significant predictors for the latent recovery score (v) in the regression analysis. These findings contradict the knowledge that mental health often intertwines with substance use, with people who are at risk for mental illness having increased risk of chronically abusing drugs (Abram, 2016; Conway, Swendsen, Husky, He, & Merikangas, 2016). The prevalence of various psychiatric disorders is not normatively low in the current sample, so the non-significant role of psychiatric disorders may not be explained by the lack of "signal" in the data. We do not have a good explanation for the counter-intuitive findings, but one thing to be noticed is that the study lasted only 12 months, and we suspect that the role of mental health in recovery may be more evident over longer periods. Also, not all psychiatric disorders are relevant in the context of recovery for a specific population; therefore, we recommend that future researchers who intend to run similar analysis to narrow their attention down to a few selected disorders. Doing so may potentially improve the model fit.

Limitations

The study was not conducted without limitations. A 12-month study period may not be long enough for studying recovery. Therefore, findings in the study may be meaningful only in the context of short-term recovery. During the study period, some participants went in and out of RHS on a regular basis, so defining RHS enrollment by attendance during the past 27 days may not be the most accurate reflection of the actual enrollment status. Although we intended to recruit people right out of their treatment for a cleaner comparison, the difficulty of recruitment forced the team to recruit a small proportion of participants after they already begun attendance at the schools. It may also be argued that dichotomizing variables in LTA is another limitation of the study. There is in fact another version of the mixture model called latent profile analysis that may be used for continuous variables, but regardless of whether continuous data or categorical data are modeled, practically there are minimal differences in the interpretation of results (Bradford, 2014). The missing data can be considered as another limitation. The missingness in the study consists of both people who were lost during follow-ups and people who refused to respond. Although all the observable missing-data mechanisms have been modeled during the imputation procedure, the current findings cannot rule out the existence of unmeasured variables that are related to the missing patterns. It is conceivable that in the process of recovery, domains of *v* may show more or less improvement at different stages of adolescents' development; yet, analyses did not examine this possibility explicitly. Finally, the RHS sample is known to have underrepresented lower socioeconomic classes and to have insufficient numbers of minority students (Tanner-Smith et al., 2018); hence, the current findings may not generalize well to racial minorities from families with lower socioeconomic statuses.

Conclusions

This study represents one of the first few attempts to operationalize recovery among adolescents. Previous studies typically addressed the issue of reporting the extend of recovery through alternative measures that are not designed for people with substance use problems, or by listing all or a few of the measures separately, where each measure is supposed to reflect recovery in some way. None of these approaches are ideal for lack of specificity or efficiency. The current study proposes an operationalization of recovery designed specifically for adolescents with substance abusing problems. By measuring the effects of treatments on a single factor *v*, one can compare the magnitude of effects of multiple programs in one take. Thus, the ability to quantify recovery using a single factor provides both a substantial economy of effort and a range of new potentials to explore in propelling the science of recovery from SUDs.

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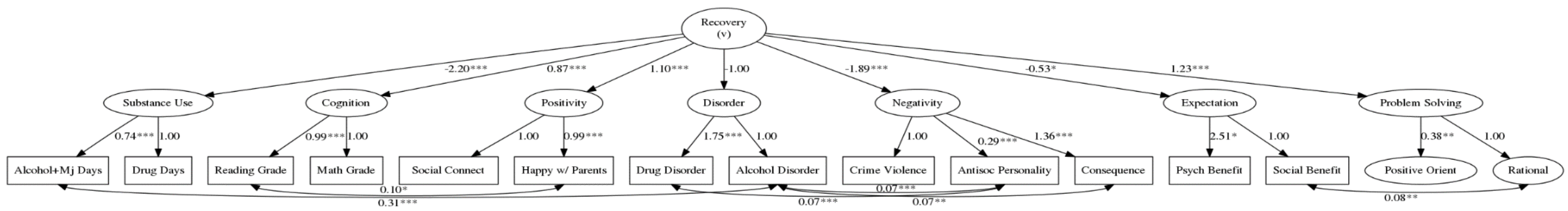
Table 1. Descriptive Statistics for Sample (*N*=294).

	Baseline		6 Months		12 Months	
Continuous Variables (Range)	*Mean (SD)*	*Missing (%)*	*Mean (SD)*	*Missing (%)*	*Mean (SD)*	*Missing (%)*
90-Day Recall of Substance Use						
Alcohol Use (0-90)	17.94 (24.58)	0 (0%)	3.69 (11.00)	56 (19%)	3.82 (9.36)	84 (29%)
Marijuana Use (0-90)	54.71 (34.50)	0 (0%)	15.88 (29.44)	56 (19%)	19.64 (30.04)	84 (29%)
Other Drug Use (0-90)	26.10 (33.32)	0 (0%)	4.64 (15.59)	56 (19%)	5.24 (14.25)	56 (29%)
Substance Use Expectancies						
Social Benefits (7-28)	21.72 (3.88)	3 (1%)	18.76 (4.81)	142 (48%)	18.67 (5.11)	147 (50%)
Psychological Benefits (5-20)	21.87 (3.63)	2 (0.7%)	20.34 (3.86)	142 (48%)	20.16 (4.13)	147 (50%)
Reading GPA (0-4)	2.61 (1.22)	2 (0.7%)	2.77 (1.03)	84 (29%)	2.78 (1.02)	120 (41%)
Math GPA (0-4)	2.25 (1.31)	2 (0.7%)	2.41 (1.15)	96 (33%)	2.61 (1.14)	140 (48%)
Crime and Violence (0-20)	2.56 (1.51)	0 (0%)	1.83 (1.49)	56 (20%)	1.69 (1.46)	84 (29%)
Social-Neighbor Connection (1-5)	2.96 (0.75)	4 (1%)	3.05 (0.70)	58 (20%)	3.09 (0.69)	85 (29%)
Personal Consequences (4-16)	9.26 (3.52)	8 (3%)	5.94 (2.72)	60 (20%)	5.83 (2.86)	122 (41%)
Youth-Parent Relationship (0-100)	58.96 (21.83)	3 (1%)	66.60 (20.85)	58 (20%)	70.81 (18.32)	86 (29%)
Peer Preference toward Drug (1-4)	3.05 (0.52)	4 (1%)	2.54 (0.59)	60 (20.4%)	2.55 (0.57)	85 (29%)
Life Satisfaction (1-5)	3.54 (0.65)	0 (0%)	3.65 (0.68)	57 (19%)	3.69 (0.67)	84 (29%)
Social Support (0-9)	8.14 (1.19)	0 (0%)	8.07 (1.28)	57 (19%)	8.11 (1.19)	84 (29%)
Categorical Variables	*n (%)*		*n (%)*		*n (%)*	
Gender[a]		0 (0%)		--		--
Female	132 (45%)		--		--	
Male	162 (55%)		--		--	
Enrolled in RHS		0 (0%)		0 (0%)		0 (0%)
No	146 (49%)		200 (68%)		241 (82%)	
Yes	148 (51%))		94 (32%)		53 (18%)	
Family Annual Income[a]		1 (0.3%)		--		--
$0 - $40,000	69 (25%)		--		--	
$40.000 - $75,000	83 (30%		--		--	
$75,000 - $100,000	44 (16%)		--		--	
> $100,000	77 (28%)		--		--	
Alcohol Disorder		0 (0%)		56 (19%)		84 (29%)
No disorder	104 (0.35)		202 (0.85)		169 (0.80)	
Abuse	45 (0.15)		18 (0.08)		17 (0.08)	
Dependence	145 (0.49)		18 (0.08)		24 (0.11)	
Other Drug Use		0 (0%)		56 (19%)		84 (29%)
No disorder	16 (0.05)		178 (0.75)		112 (0.53)	
Abuse	31 (0.11)		16 (0.07)		35 (0.17)	
Dependence	247 (0.84)		44 (0.18)		63 (0.3)	
Antisocial Personality		0 (0%)		56 (19%)		84 (29%)
No	168 (0.57)		214 (0.90)		191 (0.91)	
Yes	126 (0.43)		24 (0.10)		19 (0.09)	

[a]Variable measured only at baseline.



Confirmatory Factor Analysis (χ2/df = 1.281; Robust CFI: 0.973, Robust RMSEA 90%CI: 0.014-0.035, SRMR: 0.033)
Note: The individual error terms are omitted.

Figure 1 Second-Order Confirmatory Factor Analysis (CFA)

for Recovery.

Table 2. GEE Regression with Predicted Latent Recovery Score as Outcome.

	Unadjusted			Adjusted		
Variables	*Coef.*		*95% CI*	*Coef.*		*95% CI*
Enrollment						
non-RHS	1.00		REF	1.00		REF
RHS	-0.053	**	[-0.092, -0.015]	-0.065	**	[-0.105, 0.026]
Time						
Baseline	1.00		REF	1.00		REF
6 Months	-0.021		[-0.057, 0.015]	-0.007		[-0.040, 0.026]
12 Months	-0.036	*	[-0.073, 0.001]	-0.033	*	[-0.065, -0.002]
Time × RHS Enrollment						
6 Mon × RHS-Enrolled	0.183	***	[0.129, 0.237]	0.136	***	[0.080, 0.191]
12 Mon × RHS-Enrolled	0.159	***	[0.098, 0.220]	0.134	***	[0.077, 0.192]
Peer Preference	--		--	-0.061	***	[-0.077, -0.045]
Life Satisfaction	--		--	0.053	***	[0.037, 0.069]
Social Support			--			
No	--		--	1.00		REF
Yes	--		--	0.014	*	[0.001, 0.028]

*p<0.05, **p<0.01, ***p<0.001.

Figure 2. Interaction between RHS Enrollment and Time on Recovery

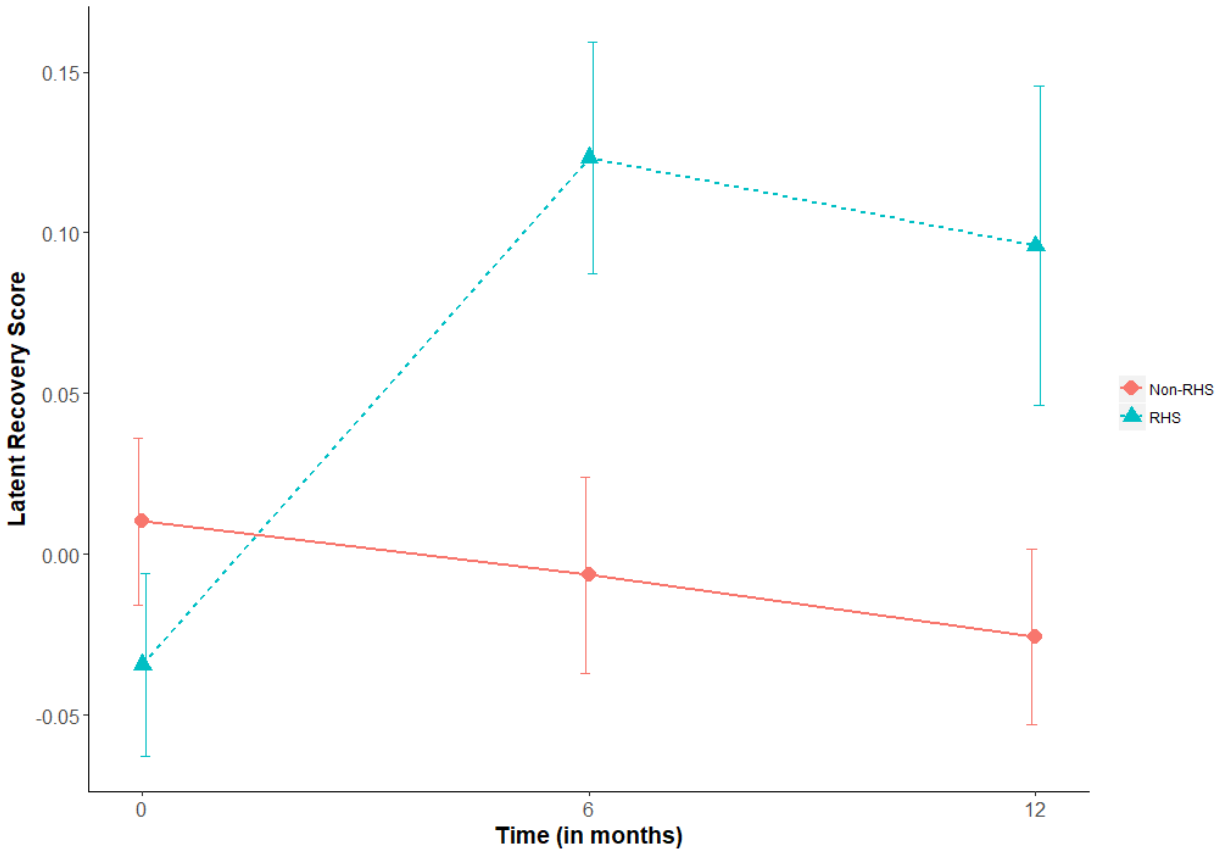


Table 3. Comparison of Models.

Number of statuses	Likelihood-ratio G^2	*df*	AIC	BIC
2	2211.99	131005	2343.99	2372.95
3	2113.39	130971	2313.39	2357.26
4	2034.32	130937	2302.32	2361.10
5	1971.79	130903	2307.79	2381.49

Table 4. Item-Response probabilities (Probability of Item Response Given Latent Status), Proportion of Latent Statuses, and Transition Probabilities in Latent Status Membership.

	Latent Recovery Status		
Parameter	Struggled Recovery	Inconsistent Recovery	Consistent Recovery
Item-Response Probabilities[a]			
Alcohol Use Disorder			
No	0.42	0.92	0.98
Yes	0.58	0.08	0.02
Alcohol Use Days			
Never	0.26	0.06	0.91
≥ 1 day	0.74	0.94	0.09
Marijuana Use Days			
Never	0.13	0.02	0.87
≥ 1 day	0.87	0.98	0.13
Drug Use Disorder			
No	0.08	0.51	0.96
Yes	0.92	0.49	0.04
Drug Use Days			
Never	0.29	0.26	0.97
≥ 1 day	0.71	0.74	0.03
Personal Consequence			
Low	0.65	1.00	0.97
High	0.35	0.00	0.03
Expected Social Benefit			
Low	0.17	0.38	0.33
High	0.83	0.62	0.67
Reading GPA			
< 3.0	0.43	0.26	0.22
≥ 3.0	0.57	0.74	0.78
Math GPA			
< 3.0	0.54	0.28	0.27
≥ 3.0	0.46	0.72	0.73
Antisocial Personality			
No	0.64	0.98	0.96
Yes	0.36	0.02	0.04
Rational Problem-Solving Skill			
Low	0.31	0.42	0.15
High	0.69	0.58	0.85
Positive Orientation Skill			
Low	0.43	0.03	0.09
High	0.57	0.97	0.91
Crime and Violence			
Low	0.45	0.86	0.83

High	0.55	0.14	0.17
Neighbor-Social Connection			
Low	0.55	0.30	0.33
High	0.45	0.70	0.67
Youth Happiness with Parents			
Low	0.36	0.07	0.16
High	0.64	0.93	0.84
Expected Psychological Benefit			
Low	0.20	0.16	0.21
High	0.80	0.84	0.79
Prevalence of statuses			
Struggled recovery group	0.99	0.00	0.01
Inconsistent recovery group	0.25	0.26	0.49
Consistent recovery group	0.25	0.43	0.32
Transitions from baseline (rows) to 6 months (columns)			
Struggled recovery group	**0.25**	0.26	0.49
Inconsistent recovery group	0.00	**0.00**	1.00
Consistent recovery group	0.06	0.39	**0.55**
Transitions from 6 months (rows) to 12 months (columns)			
Struggled recovery group	**0.81**	0.07	0.12
Inconsistent recovery group	0.00	**0.97**	0.03
Consistent recovery group	0.10	0.31	**0.59**

Note. [a]Item-response probabilities constrained to be equal at all three time points. Entries in boldface font indicate membership in the same latent status at two consecutive times. The diagonal elements marked in boldface font are probability of membership in the same latent status at two consecutive times.

Table 5. Prevalence of Latent Statuses by Baseline Enrollment.

	Latent Status		
	Struggled Recovery	Inconsistent Recovery	Consistent Recovery
Non-RHS			
Baseline	0.993	0.004	0.003
6 Months	0.344	0.274	0.382
12 Months	0.336	0.371	0.292
RHS			
Baseline	0.992	0.000	0.008
6 Months	0.132	0.253	0.615
12 Months	0.118	0.504	0.378

G^2=82.59, df=48, p=0.0014