

A LATENT PROFILE ANALYSIS OF SUBSTANCE USE AND POST-TRAUMATIC
STRESS ON SUBSTANCE USE TREATMENT OUTCOMES AMONG PEOPLE
INVOLVED WITH THE JUSTICE SYSTEM

by

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A LATENT PROFILE ANALYSIS OF SUBSTANCE USE AND POST-TRAUMATIC STRESS ON SUBSTANCE USE TREATMENT OUTCOMES AMONG PEOPLE INVOLVED WITH THE JUSTICE SYSTEM

Around 20% of people in state and local prisons meet the diagnostic criteria for both a substance use disorder and a mental health condition (Baranyi et al., 2022). The prevalence of comorbid disorders in legal populations presents a challenge for treatment initiatives prescribed in legal settings because identifying and treating concurrent substance use and mental health problems has proven difficult in practice (Back et al., 2009; Gielen et al., 2014; Johnson et al., 2015). The present study used a person-centered analysis to classify legally-involved persons in substance use treatment into mutually exclusive groups based on their clinical presentation of substance use and post-traumatic stress. Predictors of group membership were tested, and group classification was evaluated as a predictor of progress in substance use treatment, including self-reported changes in measures of treatment engagement. Rearrest rates in the 4 years following treatment were evaluated as a function of group membership. The results of this study can be used to inform screening tools, assessment protocols, and adaptive treatment models to better serve people involved with the legal system experiencing comorbid difficulties with substance use and post-traumatic stress.

I. Introduction

People involved with the legal system, including persons in prison or jail, on probation, or on parole, are 12 times more likely to suffer from a mental health condition (e.g., depression, anxiety, suicidality; Prins, 2014) and are at a heightened risk for developing a substance use disorder when compared to the general population (Fearn et al., 2016; Fovet et al., 2022). The prevalence of behavioral health concerns in legal populations constitutes a major public health

concern; for example, the healthcare needs of legal populations costs the United States an estimated 12.3 billion dollars annually (Wagner & Rabuy, 2017). Behavioral health problems, such as substance use or mental illness, have been associated with less desistance following a period of incarceration (Katsiyannis et al., 2018; Webster et al., 2015), more probation violations, rearrests, and reconvictions for people under community supervision (Yukhnenko et al., 2020), and a shorter time to recidivism among youth involved with the juvenile justice system (Aalsma et al., 2015; Wibbelink et al., 2017). With an estimated 5.5 million people under the supervision of the United States legal system (Carson & Kluckow, 2023), correctional facilities are well-positioned to address the behavioral healthcare needs of this underserved population.

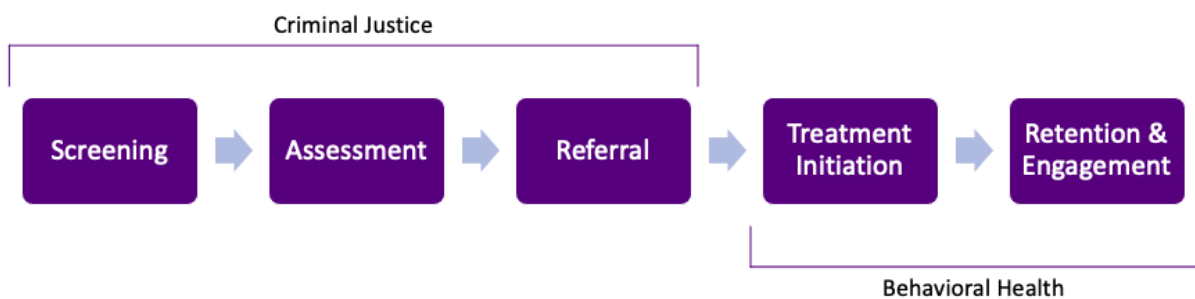
Public health initiatives designed to improve health outcomes in legal populations have led to the implementation of practices that reinforce the identification and treatment of behavioral health problems. Among these efforts, there has been an emphasis on creating *Cascade of Care* frameworks for common ailments experienced by people involved with the legal system (e.g., substance use, mental health problems, infectious disease). In brief, Cascade of Care models provide a sequential list of steps that can be used to document the number of people with a behavioral healthcare need that received treatment. For example, the Human Immunodeficiency Virus (HIV) Cascade of Care (Gardner et al., 2011) was developed to provide a system-level framework for ensuring people in need of HIV prevention or treatment services received appropriate care. Similar models have been developed for the Hepatitis C Virus (e.g., Prabhakar & Kwo, 2019; Thomas, 2020), opioid use disorder (e.g., Knight et al., 2021; Williams et al., 2017, 2019), alcohol use disorder (Mintz et al., 2021), and mental health disorders (Bunger et al., 2022). An advantage of Cascade of Care frameworks is that it provides public officials

insight into the proportion of people who received treatment as compared to the number of people identified as in need of treatment. Breakdowns along the Continuum of Care can be pinpointed, and programmatic changes can be made to maximize service delivery.

As illustrated in Figure 1, Cascade of Care models commonly include the following five steps: 1) Screening, 2) Assessment, 3) Referrals and Linkages, 4) Treatment Initiation, and 5) Treatment Retention (e.g., Belenko et al., 2017; Mugavero et al., 2013; Williams et al., 2018). In legal settings, the first three steps of this process (i.e., screening, assessment, referral), intended to identify health problems and refer clients to treatment, are often deemed the responsibility of justice staff (e.g., Dennis et al., 2019). Put another way, justice staff are responsible for screening persons on their caseload using a validated screener, providing a comprehensive diagnostic assessment for people showing an area of need, and making linkages or referrals for people with a confirmed behavioral health problem.

Figure 1

Cascade of Care



Unfortunately, organizational barriers that interfere with the implementation of evidence-based practices are common in legal settings (e.g., Belenko et al., 2018; Lehman et al., 2012; Smith et al., 2020) and can result in unmet treatment needs. For example, around 10% of justice agencies do not use an evidence-based screener for substance use and another 38% fail to screen for substance use at all (Taxman et al., 2007a, 2007b). Similar findings have been found in youth

community supervision programs; while 64% of agencies screened for substance use, only 24% provided clinical assessments (Scott et al., 2019). Screening and assessment protocols can be further complicated when a client presents with complex behavioral problems since many clinical diagnoses show a significant amount of overlap in their symptoms (e.g., Beard et al., 2016; Boschloo et al., 2015; Cramer et al., 2010). Breakdowns at the referral stage also occur in communities where there are limited treatment services available (e.g., Bird et al., 2001), or when justice staff are not aware of the available services to refer a client (e.g., Bunting et al., 2018).

The next two steps in most Cascade of Care models (i.e., treatment initiation and treatment retention) require tactful coordination between justice staff and treatment providers. The supervising officer must confirm that the client has initiated treatment and providers must engage clients early in treatment to foster adherence and retention. Regular communication between the justice and treatment systems is required to adequately monitor a client's progress in treatment and intervene when necessary. Aside from systematic barriers, including transportation, insurance access, or treatment availability (e.g., Begun et al., 2016; Owens et al., 2018; Vail et al., 2017), stigma is a widely documented client-level barrier interfering with treatment initiation for people with substance use and mental health problems (see Cerully et al., 2018 & Earnshaw, 2020 for more thorough reviews). Researchers and policymakers have attempted to redress this concern using Patient Navigation Programs and Mobile Health Units (e.g., Binswanger et al., 2015; Morano et al., 2014; Springer et al., 2022), both of which have shown reasonable efficacy and cost-effectiveness with legal populations (Taweh et al., 2021; Yu et al., 2017).

Once in treatment, providers must attempt to understand a client's goals for treatment, make programmatic adjustments to meet those goals, and engage the client early in treatment to facilitate recovery (e.g., Simpson 2000, 2004). Treatment adherence, or progress, can be assessed through a combination of biological, behavioral, and self-report assessments. For example, adherence to medication-assisted therapy for opioid use disorder can be measured using urinalysis or blood serum tests, patient interviews, and history of prescription refills (see Weiss, 2004 for a full review). Typically, progress in mental health treatment is recorded using self-report assessments that measure improvements in psychological well-being, social functioning, and psychological distress (Goodman et al., 2013). Finally, aftercare programs have been used by justice agencies to supplement positive changes made in treatment, ease a person's transition back into the community, and mitigate a client's risk for recidivism post-release (e.g., Inciardi et al., 2004; James et al., 2016; Knight et al., 1999, Wiese et al., 2023).

With the impact of behavioral health problems in legal populations, in combination with the challenge of connecting clients to treatment, it is not uncommon for people to pass through the legal system without having a need identified or receiving necessary treatment (e.g., Cropsey et al., 2012; Harty et al., 2012; Jakobowitz et al., 2017). Potential reasons for these unmet treatment needs could include, but are not limited to, organizational practices that hinder service delivery, a lack of available providers, or systematic barriers that make it difficult for persons involved with the legal system to access care. Regardless of the reason, there remains a need for empirically-driven investigations that can be used to improve organizational practices, screening tools, and assessment protocols that identify people in need of treatment with greater precision. Equally, investigations that quantify clients' needs in novel ways can provide valuable

information for adaptive treatment models intended to provide services to people in the legal system with complex behavioral problems.

The purpose of the present study was to investigate how concurrent substance use and post-traumatic stress impact clients' progress in substance use treatment. Existing literature has noted the challenges of treating clients with comorbid symptoms (Schäfer et al., 2007), and people with a comorbid substance use disorder and post-traumatic stress disorder (SUD-PTSD) benefit less from substance use treatment when compared to people without PTSD (Brown et al., 2003; Hien et al., 2000; Kubiak, 2004; Najavits et al., 2007; cf. Hildebrand et al., 2015). It remains relatively unclear, however, whether the effectiveness of treatment varies as a function of a clients' clinical presentation of substance use and post-traumatic stress. Stated differently, it could follow that unique typologies of substance use and post-traumatic stress are differentially associated with progress in substance use treatment. The current study explored this possibility using a person-centered approach to classify people into qualitatively different groups and pinpoint classes of people who are especially resistant to substance use treatment. To this end, the following pages of this proposal reviews: 1) the prevalence and associated consequences of substance use and post-traumatic stress in legal populations, 2) theoretical models used to conceptualize the etiological development of comorbid substance use and post-traumatic stress, and 3) a description of latent profile analysis, its application in this area, and an emphasis on how the use of person-centered analyses may improve public health initiatives for clients with symptoms of substance use and post-traumatic stress.

Substance Use and Post-Traumatic Stress

Around 45% of people in prison are serving time for a drug-related offense (Federal Bureau of Prisons, 2023); 20% report being under the influence of drugs or alcohol at the time of

their arrest (Center on Addiction, 2010); and more than half of the people in jail or prison meet the diagnostic criteria for a substance use disorder (Bronson et al., 2017). Substance-related difficulties have been positively associated with psychiatric symptoms, including anxiety (Lai et al., 2015), depression and suicidality (Colledge et al., 2020; Mcketin et al., 2019), and an increased all-cause mortality rate (Chang et al., 2015; Hakansson & Berglund, 2013; Hayes et al., 2011). People diagnosed with a substance use disorder are more likely to be rearrested (Zgoba et al., 2020) and return to substance use following a period of incarceration (Chamberlain & Boggess, 2019). Substance use disorders are diagnosable when someone is unable to control their substance use, spend a considerable amount of time getting, recovering from, or using substances, and show signs of physical dependence (American Psychiatric Association, 2013; DSM-V). Moreover, the DSM-V can be used to categorize someone's substance use problems as mild (2-3 symptoms), moderate (4-5 symptoms), or severe (6+ symptoms).

The rates of trauma exposure, and in turn post-traumatic symptomology, in legal populations has been well-documented (e.g., Azimi et al., 2021; Facer-Irwin et al., 2022; Liu et al., 2021; Wilson et al., 2013). A study including more than 20,000 people in prison found that 6.2% of males and 21.1% of females met the diagnostic criteria for PTSD (Baranyi et al., 2018). The DSM-V characterizes PTSD as a stress-based disorder stemming from a traumatic experience that results in psychological distress persisting at least a month (American Psychiatric Association, 2013). The diagnostic criteria for PTSD are organized into five clusters representing stressors and symptoms someone must report to receive a clinical diagnosis. The first cluster designates that a person must have been exposed to or witnessed a life-threatening event, serious injury, or sexual assault. The person must also show intrusions (e.g., flashbacks, nightmares), emotional or behavioral avoidance, changes in mood or affect (e.g., self-blame, anhedonia), and

altered physiological arousal. In around 15-30% of cases, PTSD presents alongside dissociative symptoms in the form of depersonalization (i.e., feeling detached from reality) or derealization (i.e., feeling that one's thoughts and perceptions are unreal; Stein et al., 2013; Wolf et al., 2012).

The interaction between substance use and post-traumatic stress is complicated. In other words, there exists a handful of studies showing that a trauma history is prospectively associated with substance use problems (Buckingham & Daniolos, 2013; Draucker & Mazurczyk, 2013; Kline et al., 2014), and conceptually it seems plausible that involvement with substances may place someone at a heightened risk for trauma exposure (e.g., Chilcoat & Breslau, 1998; Windle, 1994). Additionally, researchers have discerned between acute (Bryant, 2017), complex (Kliethermes et al., 2014), and developmental trauma (van der Kolk, 2005) – all of which may constitute a diagnosis of PTSD. The variability in PTSD presentation complicates treatment programs for clients with co-occurring symptoms because clients may be experiencing varying degrees of impairment (e.g., Galatzer-Levy et al., 2013; Gidzgiec et al., 2019; Panze et al., 2021). For instance, people diagnosed with SUD-PTSD and dissociative symptoms have higher treatment needs than people without dissociative symptoms (Gidzgiec et al., 2019; Killeen & Brewerton, 2022), and people with more severe trauma histories tend to report more serious substance use problems (e.g., Gallagher & Brunelle, 2023; Patel et al., 2021). Pinpointing clusters of substance use and PTSD symptoms that can predict someone's responsiveness to treatment may provide important information about the types of programs that are best suited for a particular client. For such clusters to be clinically meaningful, however, it is imperative they demonstrate a degree of conceptual clarity and ideally converge with extant theoretical frameworks used to conceptualize co-occurring substance use and PTSD. Thus, the proceeding

section will review common theoretical models used to describe the comorbid occurrence of substance use and post-traumatic stress.

Development of Comorbid of Substance Use and Post Traumatic Stress

The Self-Medication Hypothesis (SMH; Khantzian, 1987, 1997) is perhaps the most well-known theory of comorbid substance use and post-traumatic symptomology. According to this perspective, it is assumed that 1) psychoactive substances temporarily alleviate undesirable psychiatric symptoms and 2) that a person's drug of choice is directly related to their symptoms. For example, someone experiencing distressing memories, nightmares, or flashbacks following a car accident would show a proclivity towards substances that blunt the sympathetic nervous system (e.g., alcohol, benzodiazepines, opioids). In this example, the person's hypersensitive nervous system would be temporarily downregulated by their drug of choice, thereby increasing substance use via negative reinforcement. Critics of the SMH have noted the limited empirical evidence supporting the core assumptions of this approach (Manzella et al., 2015; cf. Haller & Chassin, 2014), conceptual ambiguities (Henwood & Padgett, 2007), and lack of guidance for treatment providers (Lembke, 2012). Despite this, the SMH remains one of the most well-known theories of comorbid substance use and mental health problems. Similar theories, like the Tension-Reduction Theory (Greeley & Oei, 1999) and Stress-Response Dampening Model (Sher & Levenson, 1982), have also taken the position that substance use can function as a way to ameliorate unwanted psychiatric symptoms.

Looked at differently, some theorists have conceptualized substance use as a precursor to psychiatric symptoms (Kushner et al., 1990; Zyoelnsky et al., 2003). The High-Risk Hypothesis (Windle, 1994) and Vulnerability Hypothesis (Chilcoat & Breslau, 1998), for example, posit that people who use substances are more likely to be in situations that make them vulnerable to

trauma exposure. Psychobiological approaches have also noted that the prolonged administration of many illicit substances, including opioids, cannabis, or stimulants, can lead to chemical, functional, and structural changes to the brain that undermine one's capacity to tolerate stress (e.g., Daughters et al., 2017; Gruber et al., 2009; Hirvonen et al., 2012). Particularly, the downregulation of neuroadaptations in the endocannabinoid system has been theorized as the biological mechanism responsible for the negative relationship between chronic substance use and distress tolerance (Koob & Volkow, 2016). As such, someone with low distress tolerance due to chronic substance use may be more likely to develop post-traumatic symptomology following trauma exposure because of their diminished capacity for handling stress.

The final categorization of explanations for comorbid substance use and post-traumatic stress includes theories that accentuate a third variable responsible for *both* substance use and post-traumatic stress. Such theories can be categorized under the Shared Vulnerability Hypothesis (Stewart & Conrod, 2003) which suggests a causal relationship between substance use and post-traumatic stress does not exist when accounting for their shared risk factors. Mutual risk factors for substance use and post-traumatic stress include genetic predispositions (Hruska & Delahanty, 2014; Sheerin et al., 2020), personality characteristics (e.g., anxiety sensitivity; Olatunji & Wolitzky-Taylor, 2009; Stewart & Kushner, 2001), childhood maltreatment (Gardner et al., 2019; Leza et al., 2021), and parental psychopathology (e.g., Buu et al., 2009; Yehuda et al., 2001). Notably, the Internalizing-Externalizing Liability Spectrum Model (Krueger & Markon, 2006) attempts to leverage the covariation in comorbid disorders using quantitative modeling techniques and synthesize their manifestation into shared latent dimensions (see Krueger, 1999 for an example). According to this position, the shared genetic and environmental influences of substance use and post-traumatic stress create a unique propensity towards

internalizing and externalizing symptoms that explain their comorbid clinical presentation (Kramer et al., 2014).

Latent Profile Analysis

Person-centered analyses, such as latent profile analysis, could offer an additional way to understand the interaction between substance use and post-traumatic stress in legal populations. Latent profile analysis is a mixture model technique that aims to create mutually exclusive groups (represented as latent variables) using a set of observed ordinal indicators (see Spurk et al., 2020 for a full review). Group classification is achieved under the assumption that the observed variance among study participants can be explained using latent variables that capture distinct patterns of responding. Once groups have been established, predictors and outcomes associated with class membership can be investigated (Bauer, 2022). The use of person-centered analyses is not a new concept in the behavioral sciences (see Clogg, 1981, 1995); rather, latent cluster approaches have been used to identify family dynamics associated with youths' criminal behavior (Chang et al., 2016), discrete patterns of substance use and arrest histories among people living with HIV (Shiu-Yee et al., 2018), and the clinical presentation of mental health symptoms among people in prison (Edwards et al., 2022).

Mixture model methods have been applied to substance use and post-traumatic stress to understand patterns of treatment receipt (Simpson et al., 2020), the prevalence of dissociative symptoms (Gidzgiec et al., 2019), and common coping strategies used by people with SUD-PTSD (Kearns et al., 2021). There remains a scant amount of information, however, on the interaction between substance use and post-traumatic stress in the context of substance use treatment. In one such study, Cosden et al. (2015) investigated profiles of PTSD symptoms among clients in residential substance use treatment. The authors found evidence for three

classes of post-traumatic symptomology (non-clinical, moderate, severe); men in the moderate group showed improvements in PTSD symptoms throughout treatment whereas women in the moderate group experienced an increase in trauma symptoms. Veterans in substance use treatment with internalizing symptoms had lower levels of psychosocial functioning at the start of treatment while veterans with externalizing symptoms experienced greater difficulties throughout treatment (e.g., lower program alliance, greater difficulties with other clients; Blonigen et al., 2016). In a final study, veterans with varying levels of alcohol use severity and PTSD symptoms achieved different outcomes depending on whether they were assigned to exposure therapy or an integrated coping skills intervention (Panza et al., 2021). Taken together, studies examining the effect of substance use and PTSD symptoms on treatment outcomes demonstrate the need for a more nuanced understanding of how unique combinations of substance use and PTSD symptoms influence clients' progress throughout the course of treatment.

Current Study

Using a legal sample, the current study investigated how concurrent substance use and post-traumatic stress impacted clients' responsiveness to substance use treatment. People with post-traumatic symptomology achieve worse outcomes in substance use treatment when compared to people without PTSD symptoms (Brown et al., 2003; Hien et al., 2000; Kubiak, 2004; Najavits et al., 2007). This is troublesome considering the large proportion of people in substance use treatment that report a history of trauma exposure (e.g., Giordano et al., 2016; Sanford et al., 2014; Tossone & Baughman, 2020; Wu et al., 2010). Therefore, understanding unique typologies of substance use and post-traumatic stress that predict fewer positive treatment

outcomes could provide clinicians with the information needed to better serve legally-involved persons in substance use treatment.

Aim 1 of this study sought to create latent profiles of substance use and post-traumatic stress using a sample of people who participated in a substance use treatment program between January 2017 and May 2018. The author expected that there would be a significant amount of heterogeneity in the clinical presentation of substance use and post-traumatic stress, and that latent profile analysis would be able to identify discrete profiles at the start of treatment. Aim 2 assessed how clients' baseline characteristics, including sociodemographic information, history of arrests, and physical and psychological health, were related to class membership. In accordance with the Shared Vulnerability Hypothesis, it was hypothesized that a person's risk level at the start of treatment would be associated with class membership; namely, people with more shared risk factors for SU and PTSD would be more likely to belong to the group with the most severe symptoms. Aim 3 tested how group classification was related to changes in self-reported treatment engagement, and Aim 4 determined whether changes in treatment engagement mediated the relationship between group classification and recidivism in the 4 years following treatment. The author theorized that group classification would be differentially associated with changes in treatment engagement, which in turn would predict recidivism 4-years post-treatment.

II. Method

Sample

This study collected deidentified data from people on probation who participated in a 6-month residential substance use treatment program in the Southern United States. All persons included in the study had a confirmed history of substance use and chose to participate in substance use treatment as an alternative sentencing option. The treatment program provided to

clients was a cognitive behavioral intervention that interposed maladaptive thoughts and behaviors through cognitive reframing, motivational interviewing, and behavioral modification techniques (see McHugh et al., 2010). Clients were required to participate in additional classes designed to augment substance use treatment. Additional classes provided to participants included psychoeducational activities for relapse prevention, anger management, and basic skills training. Participants were permanently housed at the correctional facility throughout the duration of treatment and received approximately 20 hours of programming each week.

Measures

Background Information

Demographic information obtained for the current study included participants' age, assigned sex at birth, and race/ethnicity. Intake and discharge dates from the facility were used to calculate the amount of time spent in treatment. Criminal history searches were used to document the number of times each participant was arrested prior to treatment.

Substance Use Severity

The Texas Christian University Drug Screen-5 (TCU DS-5; Institute of Behavioral Research, 2020) was used to measure substance use severity. The 19-item TCU DS-5 is a validated screener for substance use that was developed based on the DSM-V diagnostic criteria for substance use disorders. Example items include, "Did you use larger amounts of drugs or use them for a longer time than you planned or intended," "Did you spend a lot of time getting drugs, using them, or recovering from their use," and "Did you use drugs that put you or others in physical danger." The first 11 items are presented on a dichotomous scale (*No* = 0, *Yes* = 1) and were used to create substance use severity scores ranging from 0-11. Total scores were categorized as: 1) no substance use disorder (0-1 symptoms), 2) mild substance use disorder (2-3

symptoms), 3) moderate substance use disorder (4-5 symptoms), and 4) severe substance use disorder (6 or more symptoms). The TCU DS-5 has been validated in justice populations using classical testing theory and item response theory procedures (Knight et al., 2018; Wiese et al., 2019, 2022). The TCU DS-V was administered at Time 1 and had an internal reliability score (i.e., Cronbach's alpha) of 0.91 in the current study.

Post Traumatic Symptomology

The TCU Mental Trauma and PTSD Screen (TCU TRMAForm; Institute of Behavioral Research, 2008a) was used to assess post-traumatic symptomology. The TCU TRMAForm is a 17-item screening instrument measuring the three categories of PTSD symptoms listed in the DSM-IV: 1) Re-experiencing, 2) Avoidance, and 3) Hyperarousal. Using a 5-point Likert scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*), respondents are instructed to rate how much they have been bothered by each symptom in the past month. Sample symptoms include, "Repeated, disturbing memories, thoughts or images of a stressful experience," "Avoiding thinking about or talking about a stressful experience or avoiding feelings related to it," and "Feeling irritable or having angry outbursts" for reexperiencing, avoidance, and hyperarousal, respectively. The TCU TRMAForm has shown acceptable internal consistency ($\alpha = 0.75-0.95$) and validity in a sample of more than 1,000 legally-involved persons (Rowan-Szal et al., 2012). Total scores for the three clusters of post-traumatic symptomology were calculated by taking the sum of all items, with a higher score meaning more severe post-traumatic stress. A composite PTSD score was calculated by taking the sum of all subscales. Scores greater than 43 were categorized as above the clinical threshold for PTSD. The TCU TRMAForm was administered at Time 1 and internal reliability scores were acceptable for re-experiencing ($\alpha = 0.90$), avoidance ($\alpha = 0.87$), hyperarousal ($\alpha = 0.82$), and the composite score ($\alpha = 0.94$).

Treatment Engagement

The TCU Treatment Engagement Form (TCU ENGForm; Institute of Behavioral Research, 2007a) was used to measure changes in participants' self-reported treatment engagement. The TCU ENGForm is a 36-item instrument assessing treatment engagement in the following four areas: 1) Treatment Participation, 2) Treatment Satisfaction, 3) Counselor Rapport, and 4) Peer Support. Items are presented on a 5-point Likert scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*), with respondents instructed to rate how much they agree or disagree with each statement. Sample items include, "You are willing to talk about your feelings during counseling," "You are satisfied with this program," "Your counselor is easy to talk to," and "Other clients at this program care about you and your problems" for treatment participation, treatment satisfaction, counselor rapport, and peer support, respectively. The TCU ENGForm has demonstrated acceptable internal consistency ($\alpha = 0.75-0.92$) and validity in legal samples (Joe et al., 2007; Simpson et al., 2012). Scale scores for each treatment engagement measure were calculated by taking the mean of all items multiplied by 10. The TCU ENGForm was administered at Time 2 and Time 4, and internal reliability scores were acceptable for treatment participation ($\alpha = 0.87-0.93$), treatment satisfaction ($\alpha = 0.85-0.86$), counselor rapport ($\alpha = 0.94-0.96$), and peer support ($\alpha = 0.85-0.86$).

Physical Health & Psychological Distress

The TCU Physical and Mental Health Status Screen (TCU HLTHForm; Institute of Behavioral Research, 2008b) was used to measure participants' physical and psychological well-being at intake. Using a 5-point Likert Scale (1 = *None of the time*, 5 = *All of the time*), the TCU HLTHForm includes 11 items assessing respondents' physical health and 10 items measuring psychological distress. For physical health, respondents are instructed to rate how often they

have been bothered by physical health problems, such as “stomach problems or ulcers,” “heart disease or problems,” and “sexually transmitted infections,” in the past 12 months. Psychological distress is measured using items asking respondents how often they have been “hopeless,” “restless or fidgety,” or “depressed,” in the 30 days before administration. These forms have demonstrated strong internal consistency ($\alpha = 0.91$) and validity among legally-involved persons (Rowan-Szal et al., 2012). Physical health and psychological distress scores were calculated by taking the sum of all items within each measure. Internal reliability estimates were acceptable in the current study for both physical health ($\alpha = 0.79$) and psychological distress ($\alpha = 0.94$).

Recidivism

Public records were used to conduct criminal history searches using participants’ name and birthday. Recidivism was operationalized as any rearrest occurring in the 4 years following treatment. Arrests were measured as both a binary variable (*No* = 0, *Yes* = 1) and as the number of days to the first rearrest. Offense type (e.g., assault, robbery, etc.) and level of offense (Misdemeanor vs. Felony) were recorded for participants’ first rearrest.

Procedure

At the start of the study, the author enacted a data-sharing agreement with the participating correctional facility so that the research team at TCU could request client-level data collected from January 2017-December 2018. Client-level information that was requested included sociodemographic information (e.g., age, sex, race/ethnicity), the dates of treatment receipt, and assessments of substance use severity, post-traumatic stress, treatment engagement, physical health, and psychological health collected across four timepoints. The first timepoint was administered at intake (Time 1), the second post-orientation (Time 2), the third 4 months following intake (Time 3), and the fourth post-treatment (Time 4; i.e., about 6 months after

intake). To record rearrests and criminal history, clients' names and birthdays were shared in a datafile that was stored separately from the analytic dataset. Clients were linked between datasets using a client identification number that was assigned at intake. Client identification numbers were also used to identify people that had completed the program more than once.

Recommendations on the sample size requirements of latent profile analysis suggested at least 500 people were needed to obtain accurate parameter estimates and avoid misclassification (Vermunt, 2010). Thus, this study requested data from as many participants as possible during the specified time-period to maximize the study's statistical power and external validity. This study was approved by the Institutional Review Board at TCU prior to the start of data analysis.

Analytic Plan

The dataset was screened for missingness, outliers, and atypical responses. Descriptive statistics were generated for participants' demographic information and scale scores were calculated for all measures. Boxplots, histograms, and scatterplots were used to visualize the data.

Missingness

The author determined whether missingness in the dataset was: 1) Not Missing at Random, 2) Missing at Random, or 3) Missing Completely at Random (see Buhi et al., 2008). Incomplete data that is not random occurs when the patterns of missingness are strictly attributed to unobserved information (Gomer & Yuan, 2021). Data that is Not Missing at Random is considered the most problematic from a methodological standpoint because the missingness itself is nonignorable. Alternatively, most empirical studies assume that missingness occurs at random (Switzer & Roth, 2002, pp. 310); that is, that the missing data is strictly related to observed variables present in the dataset. The assumption of Missing at Random was partially

assessed using independent samples *t*-tests, chi-squared tests, and point-biserial correlations to evaluate whether missingness varied as a function of participants' demographic information and treatment completion. The final possibility included assuming that the data was Missing Completely at Random, which can be deduced when missingness is not related to observed variables in a dataset *or* the variables with missing data themselves (Li, 2013, pp. 795). Little's test (Little, 1988) evaluated whether incomplete values were Missing Completely at Random.

Change Scores

Change scores were calculated for measures of treatment engagement to determine how unique presentations of substance use severity and post-traumatic stress influence clients' responsiveness to substance use treatment. The simplest way to calculate change scores is the Change Score Method (see Allison, 1990), which involves taking the difference between the pretest (Y_1) and posttest (Y_2). The change score method can be achieved in a regression framework by regressing Y_2 onto an independent variable while controlling for the main effect of Y_1 (Werts & Linn, 1970). In this study, group classification was a categorical variable, thus making the change score method a statistical equivalent to a within-subjects Analysis of Variance (ANOVA; Maxwell & Howard, 1981). The change score method assumes high test-retest reliability and a low correlation between pre- and post-test scores (Bergh & Fairbank, 2002). The latter of these assumptions made the change score method potentially problematic for the current study since scores of treatment engagement and psychosocial functioning pre-treatment were likely to be highly correlated with their scores post-treatment. To account for this, effect sizes were used to evaluate clients' responsiveness to substance use treatment. The effect size statistic is calculated by taking the standardized difference between pre- and post-treatment measures thereby quantifying treatment effectiveness in standard deviation units (Hurst &

Bolton, 2004, pp. 27). The effect size of treatment was interpreted as small ($d = 0.20$), medium ($d = 0.50$), or large ($d \geq 0.80$; Cohen, 1977), with group classification being considered a predictor of treatment effectiveness. For reference, meta-analytic procedures have shown that cognitive behavioral interventions for substance use generally yield moderate effect sizes ($d = 0.45$; McHugh et al., 2010, pp. 512).

Latent Profile Analysis

The tidyLPA package (Rosenberg et al., 2018) in RStudio was used to conduct latent profile analysis and determine whether heterogeneous presentations of substance use and post-traumatic stress were present at the start of treatment (i.e., Aim 1). Items on the TCU DS-5 were combined to create four indicators of substance use (i.e., unsuccessful control, risky use, psychosocial problems, withdrawal) and the TCU TRMAForm was used to generate three indicators of PTSD (i.e., re-experiencing, avoidance, hyperarousal). All variables were mean-centered to ease the interpretation of study results.

A series of models testing a different number of latent profiles were estimated simultaneously to find the model that best fits the data. The class-invariant parameterization method was used as the model specification criteria whereby the variance across profiles was set to equal and the covariances were restricted to zero (see Pastor et al., 2007 for a review on model specification methods). Latent profiles were evaluated using a combination of model fit statistics (e.g., AIC, BIC), certainty statistics (e.g., entropy), and conceptual clarity. The AIC and BIC statistics are perhaps the most commonly used measures of model fit for latent profile analysis, with lower scores representing better fitting models. The measure of entropy served as an uncertainty diagnosis, which describes how confident the model is that each person in the dataset belongs to a single profile. Uncertainty scores greater than 0.80 were deemed acceptable for the

present study (Weller et al., 2020). Class membership was depicted visually using a profile plot that displayed a standardized mean value for each profile on all measures that defined class membership.

To further understand the latent profiles, a between-subjects ANOVA tested for mean differences in substance use and post-traumatic stress among the latent profiles. Significant models were unpacked using Bonferroni's correction with a critical value of .01 to determine statistical significance (see Armstrong, 2014). Using group means and standard deviations, effect sizes (i.e., Cohen's *d*) were calculated for the largest pairwise comparisons.

Predictors and Outcomes of Profile Membership

Predictors and distal outcomes associated with profile membership were examined (i.e., Aims 2 and 3). Predictors of group membership were tested using multinomial logistic regression. The categorical variable defining profile membership was entered into the model as the dependent variable and participants' demographic information, history of arrests, and physical and psychological health at baseline were entered into the model as predictors. The Likelihood Ratio Chi-Square test determined how well the overall model fit the data, with significant results suggesting the model with predictors was an improvement from the null model (i.e., model with no predictors). Regression estimates for each predictor were interpreted while controlling for other variables in the model and expressed as both multinomial regression coefficients and odds ratios (with a 95% confidence interval).

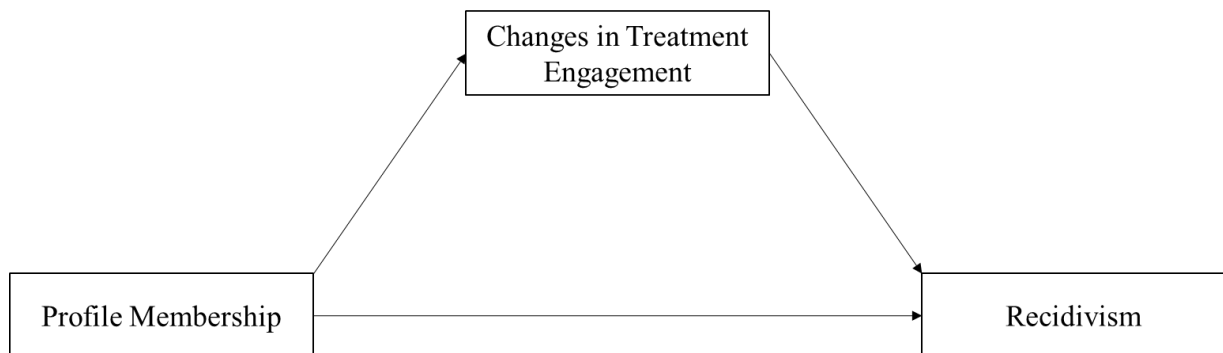
Aim 3 sought to determine whether profile membership was differentially associated with engagement in substance use treatment – as indicated by measures of engagement at Time 2, Time 4, their raw change over time, and their standardized change over time. This aim was tested using a Multivariate Analysis of Variance (MANOVA) where measures of treatment

engagement served as outcome variables and class membership served as the independent variable. A MANOVA was specifically used because the four dependent variables were expected to be correlated. Thus, within a MANOVA framework, the model can detect patterns of results among the dependent variables while simultaneously lessening the probability of committing a Type I error (see Warne, 2014). Omnibus F tests were unpacked using Tukey's HSD with a critical value of .05 to determine statistical significance.

The final set of analyses were performed to test Aim 4 and determine whether clients' responsiveness to substance use treatment mediated the relationship between profile membership and recidivism in the four years following treatment (see Figure 2). Using the lavaan package (Rosseel, 2012), the indirect effect of profile membership on recidivism through changes in treatment engagement was estimated. Profile membership was tested as a predictor of treatment effectiveness, and then changes in treatment engagement were evaluated as a predictor of recidivism while controlling for class membership. The author planned to estimate the indirect effect using 10,000 bootstrap reiterations and a 95% confidence interval (Shrout & Bolger, 2002). All analyses described herein were performed in RStudio and SPSS version 29.

Figure 2

Theorized Path Model



III. Results

There were 1,447 people that completed the intake process between January 2017-December 2018. To ensure sufficient time for program completion, these data were filtered so that only people who had completed the intake prior to May 2018 were in the dataset. This specification reduced the sample size to 1,063 people that theoretically could have completed their treatment by December 2018. Since clients could have completed the treatment program more than once, duplicate responses were identified using client IDs. Duplicate responses showed an inconsistent and unintuitive pattern when examining the dates and scores of various self-report measures. For example, several clients had intake assessments administered on the same date with different mean levels of substance use severity (e.g., 2 vs. 11). This pattern prevented the author from adopting the approach of simply “taking the first response.” The author deduced that these responses were likely coding errors when entering client IDs, since all data were entered manually. Therefore, clients with duplicate IDs were removed from the dataset to avoid retaining inconsistent or unreliable datapoints. The resultant dataset consisted of 931 people who had participated in the substance use treatment program once between January 2017 and December 2018.

Missingness

Descriptive statistics for the TCU DS-V and TCU TRMAForm showed that 92.2% of the data at Time 1 were complete. More precisely, 86.5% of the sample had complete data for both measures, 7.5% were missing values on the TCU TRMAForm, 4.4% were missing values on the TCU DS-V, and 1.4% were missing values for both TCU TRMAForm and TCU DS-V. Little’s test suggested that these data were not Missing Completely at Random, $\chi^2(80) = 159.00, p < .001$. To assess potential sources of missingness, *t*-tests, chi-squared tests, and a point-biserial correlation evaluated whether participants’ demographic information and treatment completion

were related to missingness. These results showed that age, sex (Male vs. Female), race (White vs. Black, Indigenous, People of Color [BIPOC]), and treatment completion (Yes vs. No) were unrelated to missingness, $ps \geq .372$.

Visually examining the pattern of missingness showed that missing data was likely due to inconsistent reporting of participants' responses. For example, there were a different number of responses on the TCU DS-V and TCU TRMAForm (e.g., 877 vs. 848) at Time 1 despite this being theoretically impossible. Put another way, all people who enter the program are administered Time 1 assessments, and therefore, the total number of people who completed each survey should be identical. This inconsistency led the researcher to conclude that, since all responses were manually entered, some responses may have been accidentally omitted from the raw dataset. Additionally, this possibility provides an explanation as to why demographic information and program completion were not related to missingness. The patterns of missingness were not related to some unobserved variable; rather, the missing data was a function of clients' responses not being recorded. Thus, the remaining analyses were performed using the 807 people who had complete data on the TCU DS-V and TCU TRMAForm at Time 1.

Descriptive Statistics

The final sample consisted of 807 people who participated in substance use treatment between January 2017 and December 2018 (see Table 1). There were 617 (76.5%) people who completed Time 2 assessments (i.e., post-orientation), 545 (67.5%) people that completed Time 3 assessments (i.e., during treatment), and 543 (67.3%) people that completed Time 4 assessments (i.e., post-treatment). There were 436 (54.0%) people that had complete data across all four timepoints. The average age of respondents at the start of treatment was 33.56 ($SD = 10.57$). Participants were mostly male ($n = 568, 70.4%$) and White ($n = 324, 40.1%$). Five

hundred and fifty-six (68.9%) people were listed as having completed the program, 164 (20.3%) escaped, and 87 (10.8%) were discharged prematurely (i.e., medical, disciplinary). The average time spent in treatment for people that completed the program was 150 ($SD = 35.70$) days or about 5 months. Half ($n = 417$, 51.7%) of the sample had a severe substance use disorder and one-third ($n = 301$, 37.3%) were above the clinical threshold for PTSD. Of the 439 people who were rearrested, the average amount of time to first arrest was 525 days ($SD = 416.94$), with 248 (56.5%) felony offenses and 191 (43.5%) misdemeanor offenses.

Table 1

Participant Background Information (N = 807)

	<i>n</i>	%
Sex		
Male	568	70.4%
Female	239	29.6%
Race/Ethnicity		
Black/African American	213	26.4%
Hispanic	234	29.0%
Multiracial	7	0.9%
White	324	40.1%
Another race/ethnicity	28	3.4%
Missing	1	.01%

Table 1 (continued)

	<i>n</i>	%
Discharge Reason		
Successful Completion	556	68.9%
Escape	164	20.3%
Other	87	10.7%
Substance Use Disorder		
None	184	22.8%
Mild	102	12.6%
Moderate	104	12.9%
Severe	417	51.7%
Post-Traumatic Stress Symptoms		
Below Clinical Threshold	506	62.7%
Above Clinical Threshold	301	37.3%

Note. Numbers represent totals and percentages.

Latent Profile Analysis

Aim 1 intended to pinpoint clusters of people who shared similar typologies of substance use and PTSD symptomology. Latent profiles were estimated using the class-invariant parameterization method. More complex models were also considered by estimating additional parameters; however, the simplest estimation method provided the most conceptually meaningful results. This model considered between 1-8 possible profiles and were compared using measures of model fit and entropy. As illustrated in Table 2, the results showed that the model with five classes best fit the data. Visual inspection of the profile plot, however, revealed that two of the

classes contained means that were not different enough to be conceptually meaningful. In contrast, the model with four classes provided a more parsimonious and conceptually clear solution. As shown in Figure 3, the first class ($n = 255$) was characterized by high substance use and low post-traumatic symptomology. The second class ($n = 115$) reported low substance use and high trauma, whereas the third class ($n = 165$) endorsed high substance use and high trauma. The final class ($n = 272$) was characterized by low substance use and low trauma. The uncertainty diagnosis for the four-profile model was .90, suggesting that the model was 90% certain that each participant belonged to a single profile. The posterior probability distribution was used to create an observed categorical variable representing profile membership, which assigned everyone in the dataset to one of the four classes.

Table 2

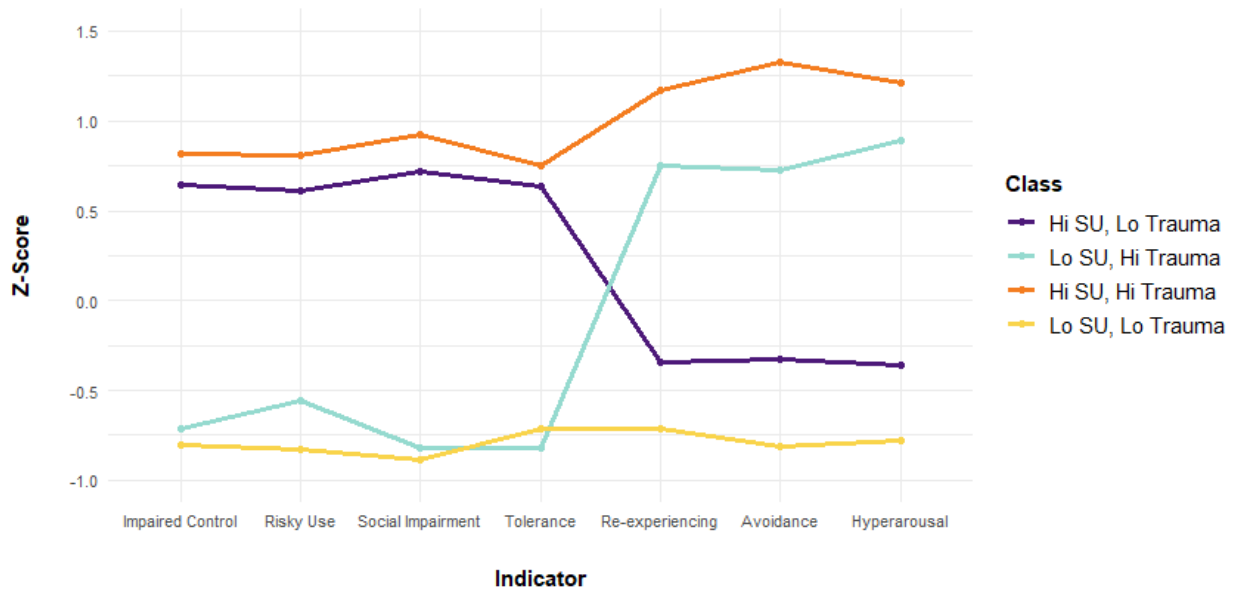
Latent Profile Analysis of Substance Use and Post-Traumatic Stress (N = 807)

Class Specified	AIC	BIC	Entropy	Group Prevalence				
				1	2	3	4	5
1	25431.13	25496.83	--	1.00	--			
2	23422.76	23526.01	0.91	0.50	0.50	--		
3	22856.06	22996.86	0.88	0.31	0.44	0.25	--	
4	22208.39	22386.73	0.90	0.32	0.14	0.20	0.34	--
5	22011.07	22226.96	0.88	0.21	0.18	0.13	0.28	0.20

Note. Bold indicates best fitting solution.

Figure 3

Observed Means of Substance Use and Post-Traumatic Stress for Participants at Baseline



Note. SU = Substance Use, Hi = High, Lo = Low.

Table 3 displays the means and standard deviations for the generated profiles on measures of substance use and post-traumatic stress. A one-way between-subjects ANOVA tested for an effect of Class (Class 1, Class 2, Class 3, Class 4) on measures of substance use and post-traumatic stress. All models were statistically significant, $F_s(3803) \geq 282.65$, $ps \leq .01$, $\eta^2_s \geq 0.51$, and were unpacked using Bonferroni's correction with a critical value of .01. Follow-up tests showed that, on measures of impaired control and physical dependence, Class 1 (high substance use, low trauma) did not significantly differ from Class 3 (high substance use, high trauma). Likewise, Class 2 (low substance use, high trauma) and Class 4 (low substance use, low trauma) did not differ in their self-reported impaired control or physical dependence. Classes 2 and 4 did not differ on social impairment and Classes 1 and 3 reported comparable levels of risky use. All other pairwise comparisons were statistically significant, $ps \leq .01$.

Table 3*Means and Standard Deviations for Substance Use and Post-Traumatic Stress for Latent Profiles*

	Hi SU, Low Trauma (<i>n</i> = 255)	Low SU, Hi Trauma (<i>n</i> = 115)	Hi SU, Hi Trauma (<i>n</i> = 165)	Low SU, Low Trauma (<i>n</i> = 272)	Test of Group Difference	Cohen's <i>d</i> for largest pairwise difference
	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)		
Impaired Control	3.22 (1.01) ^a	1.10 (1.15) ^b	3.50 (0.85) ^a	0.95 (1.16) ^b	$F(3,803) = 334.15$	2.09
Social Impairment	2.35 (0.79)	0.46 (0.61) ^c	2.59 (0.69)	0.37 (0.55) ^c	$F(3,803) = 631.56$	3.55
Risky Use	1.48 (0.68) ^d	0.47 (0.65)	1.65 (0.54) ^d	0.24 (0.51)	$F(3,803) = 303.02$	2.68
Withdrawal/Tolerance	1.56 (0.62) ^e	0.30 (0.51) ^f	1.65 (0.56) ^e	0.39 (0.63) ^f	$F(3,803) = 282.65$	2.52
Cluster B	9.62 (3.55)	16.08 (5.45)	18.54 (4.32)	7.52 (2.94)	$F(3,803) = 352.49$	2.98
Cluster C	13.68 (4.49)	21.47 (4.78)	25.85 (4.11)	10.15 (3.32)	$F(3,803) = 598.54$	4.20
Cluster D	10.05 (3.24)	16.79 (3.68)	18.51 (3.49)	7.79 (2.65)	$F(3,803) = 509.23$	3.46

Note. Means with same superscripts did not significantly differ ($p > .01$). All other comparisons were significantly different ($p < .01$). *M* = Mean, *SD* = Standard Deviation, Hi = High, Lo = Low, SU = Substance Use.

Predictors of Group Classification

A multinomial logistic regression examined participants' age, sex (male [dummy-coded = 0], female), race (BIPOC [dummy-coded = 0], White), prior arrests, physical health, and psychological distress as predictors of group classification (see Table 4). The high substance use, high trauma class (Class 3) was coded as the reference group to which all other classes were compared to. The Likelihood Ratio Chi-Squared test was significant, $\chi^2(18) = 5034.29, p \leq .01$, indicating the model with predictors was an improvement over the null model. The only sociodemographic characteristic that discriminated between profiles was age, and psychological distress was the only risk variable related to class membership. For every one-unit increase in age, the odds of belonging to the low substance use, high trauma condition (Class 2) increased by a factor of 1.04 (1.00-1.07) when compared to the high substance use, high trauma condition. As compared to Class 3, every one-unit increase in psychological distress decreased the odds of belonging to Class 1, Class 2, and Class 4 by a factor 0.82 (0.79-0.85), 0.94 (0.91-0.97), and 0.73 (0.70-0.77), respectively. The results also showed that sex and psychological distress discerned between profile membership when Class 1 was set as the reference category. Specifically, sex was related to being in Class 4 ($b = 0.46, SE = 0.23, p = .048$), and psychological distress was related to being in Class 2 ($b = 0.14, SE = 0.02, p \leq .01$) and Class 4 ($b = -0.11, SE = 0.02, p \leq .01$). Being male increased the odds of belonging to Class 4 by a factor of 1.58 (1.00, 2.18). For every one unit increase in psychological distress, the odds of belonging to the Class 2 increased by a factor of 1.15 (1.11-1.20) and decreased the odds of belonging to Class 4 by a factor of 0.90 (0.87-0.93). In the final comparison, when Class 2 was coded as the reference category, psychological distress was related to profile membership when compared to Class 4 ($b = -0.25,$

Table 4*Multinomial Logistic Regressions of the Association Among Sociodemographic, Risk Variables, and Profile Membership*

	High SU, Low Trauma		Low SU, High Trauma		Low SU, Low Trauma	
	<i>B (SE)</i>	Odds ratio (95% CI)	<i>B (SE)</i>	Odds ratio (95% CI)	<i>B (SE)</i>	Odds ratio (95% CI)
Demographics						
<i>Age</i>	0.01 (0.02)	1.01 (0.98-1.04)	0.04 (0.02)*	1.04 (1.00-1.07)	0.03 (0.02)	1.03 (0.99-1.06)
<i>Sex (Male)</i>	-0.11 (0.28)	0.90 (0.53-1.54)	-0.24 (0.28)	0.79 (0.46-1.36)	-0.56 (0.31)	0.57 (0.31-1.06)
<i>Race (BIPOC)</i>	0.29 (0.27)	1.33 (0.79-2.25)	-0.24 (0.27)	0.79 (0.46-1.34)	-0.10 (0.30)	0.91 (0.51-1.63)
Risk Variables						
<i>Prior Arrests</i>	-0.03 (0.03)	0.97 (0.93-1.02)	-0.02 (0.02)	0.98 (0.94-1.03)	-0.03 (0.03)	0.97 (0.92- 1.02)
<i>Physical Health</i>	-0.04 (0.02)	0.96 (0.92-1.01)	0.004 (0.02)	1.00 (0.97-1.04)	-0.01 (0.03)	0.99 (0.94-1.04)
<i>Psychological Distress</i>	-0.20** (0.02)	0.82 (0.79-0.85)	-0.06** (0.02)	0.94 (0.91-0.97)	-0.31** (0.02)	0.73 (0.70-0.77)

Note. All membership profiles were compared to high substance use, high trauma, $\chi^2(18) = 504.29, p \leq .001$. *B* = standardized coefficient; *SE* = Standard Error; CI = Confidence Interval; BIPOC = Black, Indigenous, People of Color; SU = Substance Use. * $p < .05$, ** $p < .001$.

$SE = 0.02, p \leq .01$). Every one-unit increase in psychological distress decreased the odds of belonging to Class 4 by a factor of 0.78 (0.74-0.81).

Outcomes of Group Classification

Aim 3 of this study examined how profile membership was related to clients' self-reported treatment engagement. Table 5 displays the descriptive statistics for the treatment engagement measures collected at Time 2, Time 4, their raw change over time, and their standardized change over time. The results did not change when considering the standardized change scores as compared to the raw change scores; thus, for ease of interpretation, the results involving changes in treatment engagement are reported using their raw change over time.

Table 5

Descriptive Statistics for Measures of Treatment Engagement

	Time 2 ($n = 617$)	Time 4 ($n = 536$)	Raw Change Score ($n = 468$)	Standardized Change Score ($n = 468$)
Treatment Participation	42.23 (5.05)	42.88 (5.63)	0.35 (5.68)	0.04 (1.45)
Counselor Rapport	40.49 (6.98)	40.62 (7.85)	-0.23 (8.25)	0.28 (1.00)
Treatment Satisfaction	35.56 (7.94)	35.23 (8.59)	-0.50 (7.99)	0.03 (1.03)
Peer Support	34.59 (8.70)	36.76 (8.47)	2.14 (9.29)	0.23 (0.99)

Note. Numbers represent means, standard deviations are in parentheses.

A MANOVA showed that profile membership was related to all treatment engagement assessments at Time 2, $F_s(3,613) \geq 3.20, p_s \leq .023, \eta^2_s < .01$, and their raw change over time, $F_s(3,464) \geq 4.39, p_s \leq .01, \eta^2_s \leq .04$. In contrast, profile membership was only related to self-reported peer support at Time 4, $F(3,532) = 5.57, p < .01, \eta^2_s < .01$. At Time 2, Class 1 (high substance use, low trauma) and Class 2 (low substance use, high trauma) differed on all

assessments of treatment engagement (see Table 6). People that were in the low substance use, high trauma class reported lower levels of treatment participation, counselor rapport, treatment satisfaction, and peer support than people in the high substance use, low trauma class.

Additionally, Class 4 (low substance use, low trauma) reported higher levels of treatment participation, counselor rapport, and peer support than Class 3. All other pairwise comparisons were non-significant ($ps > .05$). Profile membership was also found to be related to participants' self-reported peer support at Time 4. People in Class 1 and Class 3 reported higher levels of peer support when compared to Class 4. Moreover, people in Class 3 endorsed higher levels of peer support when compared to Class 2.

Table 6

Measures of Treatment Engagement at Time 2 and Time 4 among Latent Profiles

	Class 1 (<i>n</i> = 185)	Class 2 (<i>n</i> = 82)	Class 3 (<i>n</i> = 129)	Class 4 (<i>n</i> = 221)
Time 2				
Treatment Participation	42.42 (4.77) ^a	40.67 (6.01) ^{ab}	41.76 (4.89)	42.92 (4.84) ^b
Counselor Rapport	41.17 (6.22) ^a	38.18 (8.02) ^{ab}	39.85 (7.65)	41.16 (6.59) ^b
Treatment Satisfaction	36.54 (6.88) ^a	33.31 (8.55) ^a	35.42 (8.09)	35.65 (8.09)
Peer Support	35.90 (7.61) ^a	31.28 (10.06) ^{ab}	34.20 (9.31)	34.96 (8.70) ^b
Time 4				
Treatment Participation	42.93 (5.38)	42.57 (5.86)	43.84 (4.78)	42.45 (6.11)
Counselor Rapport	40.75 (7.42)	40.57 (8.32)	42.01 (6.42)	39.84 (8.62)
Treatment Satisfaction	35.51 (7.97)	34.76 (9.62)	36.59 (7.70)	34.48 (9.10)

Table 6 (continued)

Time 4	Class 1 (<i>n</i> = 171)	Class 2 (<i>n</i> = 72)	Class 3 (<i>n</i> = 98)	Class 4 (<i>n</i> = 195)
Peer Support	38.01 (7.13) ^{ab}	34.58 (10.33) ^{ac}	38.49 (7.95) ^{cd}	35.59 (8.76) ^{bd}

Note. Numbers represent means, standard deviations are parentheses. Rows with same superscripts differed significantly by Tukey's HSD ($p = .05$). Class 1 = high substance use, low trauma; Class 2 = low substance use, high trauma; Class 3 = high substance use, high trauma; Class 4 = low substance use, low trauma.

Change scores in treatment engagement were evaluated as a function of profile membership (see Table 7). Class 2 (low substance use, high trauma) and Class 3 (high substance use, high trauma) showed a change in treatment participation, counselor rapport, and treatment satisfaction that was significantly different from people in Class 4 (low substance use, low trauma). For peer support, the only significant difference among latent profiles was between Class 3 and Class 4; people in the high substance use, high trauma condition experienced a larger positive change in peer support during treatment when compared to people in Class 4.

Table 7

Mean Change Scores on Measures of Treatment Engagement among Latent Profiles

	Class 1 (<i>n</i> = 143)	Class 2 (<i>n</i> = 59)	Class 3 (<i>n</i> = 90)	Class 4 (<i>n</i> = 176)	Total Change
Treatment Participation	0.50 (5.72)	1.67 (5.50) ^a	1.81 (5.31) ^b	-0.97 (5.63) ^{ab}	0.35 (5.68)
Counselor Rapport	-0.41 (8.42)	1.96 (8.27) ^a	2.02 (7.74) ^b	-1.97 (7.99) ^{ab}	-0.23 (8.25)
Treatment Satisfaction	-0.74 (7.29)	1.60 (7.78) ^a	1.13 (8.60) ^b	-1.84 (8.06) ^{ab}	-0.50 (7.99)
Peer Support	2.68 (8.20)	2.83 (9.68)	4.80 (10.01) ^a	0.11 (9.23) ^a	2.14 (9.29)

Note. Numbers represent means, standard deviations are parentheses. Rows with same superscripts differed significantly by Tukey's HSD ($p < .05$). Class 1 = high substance use, low

trauma; Class 2 = low substance use, high trauma; Class 3 = high substance use, high trauma; Class 4 = low substance use, low trauma.

Given the differences in treatment engagement between subjects, it seemed necessary to also explore differences in treatment engagement within subjects. Thus, as an unplanned post-hoc analysis, a 2 (Time: Time 2 vs. Time 4) x 4 (Class: Class 1 vs. Class 2 vs. Class 3 vs. Class 4) Mixed Method ANOVA was used to test for significant differences in measures of treatment engagement across time (see Table 8). The interaction between Time and Class was statistically significant for all measures of treatment engagement, $F_s(3,464) \geq 4.39, p_s < .001, \eta_p^2 \leq .04$. Simple main effects analyses were used to decompose these interactions and comparisons were made using Bonferroni's correction with a critical value of .05. The results revealed that within Classes 2, 3, and 4, treatment participation scores reported at Time 4 were significantly different from that at Time 2 ($p_s \leq .022$). When examining counselor rapport as the dependent variable, Time 2 scores were significantly different from Time 4 scores within Classes 3 and 4 ($p_s \leq .018$). In contrast, the only significant difference between Time 2 and 4 treatment satisfaction was within Class 4 ($p = .002$). Classes 1, 2, and 3, reported significantly different levels of peer support at Time 2 when compared to Time 4 ($p_s \leq .018$). In general, the changes in treatment engagement observed across time were statistically significant for Classes 2, 3, and 4.

Table 8

Within-Class Variation among Measures of Treatment Engagement across Time

	Class 1 (<i>n</i> = 143)	Class 2 (<i>n</i> = 59)	Class 3 (<i>n</i> = 90)	Class 4 (<i>n</i> = 176)
Treatment Participation				
Time 2	42.38 (0.41)	41.16 (0.64) ^a	42.04 (0.52) ^b	43.32 (0.37) ^c
Time 4	42.88 (0.48)	42.83 (0.75) ^a	43.85 (0.60) ^b	42.35 (0.43) ^c

Table 8 (continued)

	Class 1 (<i>n</i> = 143)	Class 2 (<i>n</i> = 59)	Class 3 (<i>n</i> = 90)	Class 4 (<i>n</i> = 176)
Counselor Rapport				
Time 2	40.94 (0.54)	39.00 (0.85)	40.06 (0.69) ^d	41.64 (0.49) ^e
Time 4	40.53 (0.67)	40.96 (1.04)	42.08 (0.84) ^d	39.67 (0.60) ^e
Treatment Satisfaction				
Time 2	36.28 (0.65)	33.73 (1.01)	35.68 (0.82)	36.05 (0.59) ^f
Time 4	35.54 (0.72)	35.33 (1.12)	36.81 (0.91)	34.21 (0.65) ^f
Peer Support				
Time 2	35.41 (0.71) ^g	32.09 (1.11) ^h	34.27 (0.90) ⁱ	35.34 (0.64)
Time 4	38.10 (0.69) ^g	34.92 (1.07) ^h	39.07 (0.87) ⁱ	35.45 (0.62)

Note. Numbers represent means (standard errors). Within measures of treatment engagement, rows with same superscripts represent significant differences between Time 2 and Time 4 for each class.

Mediation Analysis

The final aim of this study sought to determine whether changes in treatment engagement served as a mediator explaining the relationship between profile membership and recidivism following treatment. To this end, descriptive statistics for participant rearrests rates (Yes vs. No) in the 4 years post-treatment were evaluated to further understand the trajectory of rearrests across time. One-hundred and twelve (13.9%) people were rearrested within 6 months of their release, 197 (24.4%) 1-year post-release, 309 (38.3%) 2 years post-release, 377 (46.7%) 3 years post-release, and 439 (54.5%) 4 years post-release. People who completed the substance use treatment program ($M = 620.89$, $SD = 408.14$) had a larger number of days to their first rearrest

when compared to people that had been prematurely discharged for any reason ($M = 388.70$, $SD = 391.54$), $t(434) = 5.94$, $p \leq .01$.

Profile membership was related to changes in all assessments of treatment engagement, $F_s(3464) \geq 4.39$, $p_s < .01$; Class 2 and Class 3 showed greater positive change in treatment participation, counselor rapport, and treatment participation than Class 4, and Class 3 showed a greater change in peer support than Class 4. However, changes in treatment engagement were not related to rearrests, defined as the number of days to first rearrest, for people rearrested within 6 months, 1 year, 2 years, 3 years, or 4 years following treatment ($p_s > .05$). Looking at differently, a binary logistic regression also showed that changes in treatment engagement were not related to recidivism (Yes vs. No) for people rearrested within the four years post-treatment ($p_s > .05$). These results suggest that while profile membership was differentially associated with self-reported changes in treatment engagement, the changes in treatment engagement were not related to recidivism. Changes in treatment engagement did not mediate the relationship between profile membership and recidivism in the four years post-treatment.

IV. Discussion

People involved with the legal system are at a heightened risk for developing a substance use disorder (Fearn et al., 2016; Fovet et al., 2022) and have an increased chance of suffering from a mental health condition when compared to the general population (Prins, 2014). Challenges with substance use and mental health contribute to diminished physical and psychological health in legal samples (Colledge et al., 2020; Mcketin et al., 2019) and constitute a major risk for recidivism (Wallace & Wang, 2020; Yukhnenko et al., 2020). Moreover, people with concurrent substance use and mental health problems encounter a unique set of challenges when transitioning back into the community (Johnson et al., 2015) and are at a greater risk for

recidivism post-release (Baillargeon et al., 2010). People with comorbid substance use and post-traumatic stress, in particular, have been shown to be less responsive to substance use treatment (Brown et al., 2003; Hien et al., 2000; Kubiak, 2004; Najavits et al., 2007), placing these clients especially at-risk for challenges with substance use during reentry. As such, empirical investigations are needed to uncover how co-occurring substance use and post-traumatic stress affects clients participating in substance use treatment. The implications of such studies could include the identification of persons that may be resistant to substance use treatment and recommendations for the field that can improve outcomes for persons in the legal system with complex behavioral problems.

The purpose of the current study was to investigate the impact of concurrent substance use and post-traumatic stress on legally-involved persons' progress in substance use treatment. Latent profile analysis was used to quantify participants' substance use and post-traumatic stress and generate mutually exclusive groups representing unique typologies of substance use and post-traumatic stress (Aim 1). Predictors of class membership were evaluated to uncover characteristics predictive of participants' clinical presentation at the start of treatment (Aim 2). Aim 3 sought to identify groups of people that were particularly resistant to an in-prison substance use treatment program. Profile membership was considered as a predictor of participants' self-reported treatment engagement post-orientation (i.e., Time 2), post-treatment (i.e., Time 4), and their raw change over time. The final aim of this study considered changes in treatment engagement as a mechanism explaining the relationship between profile membership and recidivism in the four years following treatment.

Descriptive statistics were available for 807 people participating in an in-prison substance use treatment program. Approximately three-fourths (77.2%) of the sample had a diagnosable

substance use disorder, as indicated by the TCU DS-V, and one-third (37.3%) of the sample were above the clinical threshold for PTSD—per the TCU TRMAForm. These estimates are elevated when compared to larger studies estimating the prevalence of substance use and post-traumatic stress among legally-involved persons. For example, Fazel et al. (2017) reported that 30% of males and 50% of females in prison had a substance use disorder, and Baranyi et al. (2018) found the pooled estimate for PTSD among incarcerated persons to be 6.2% for men and 21.1% for women. The present study recruited participants from a facility working exclusively with clients who have a history of substance use, which may account for the elevated incidence of substance use disorders in the current sample. The incidence of people above the clinical threshold for PTSD also demonstrates the relatively high proportion of people assigned to an in-person substance use treatment who are experiencing comorbid symptoms. These results, in combination with extant investigations (Giordano et al., 2016; Sanford et al., 2014; Tossone & Baughman, 2020; Wu et al., 2010), demonstrate the need for in-prison treatment programs that can address both substance use and PTSD symptoms in legal populations.

Latent profile analysis showed that there were four distinct typologies of substance use and post-traumatic stress: 1) high substance use, low trauma; 2) low substance use, high trauma; 3) high substance use, high trauma; and 4) low substance use, low trauma. These results diverge from other studies in this area finding that a three-class solution best explained participants' psychiatric symptoms (i.e., low, moderate, high; Blonigen et al., 2016; Cosden et al., 2015; Panza et al., 2021). The four-class model obtained in the current study could be a byproduct of including both substance use and post-traumatic stress symptoms into the same model. Indeed, it has been more common for studies to quantify substance use symptoms in people with PTSD (e.g., Blonigen et al., 2016) or post-traumatic symptomology for people in substance use

treatment (e.g., Cosden et al., 2015). The addition of substance use and PTSD symptoms into the same model could have resulted in a larger amount of variability, thereby resulting in a more complex solution. Alternatively, these results may also be attributed to the resultant sample; people involved with the legal system may be inherently different from samples recruited from residential treatment programs or Veterans Affairs. Nevertheless, the results associated with Aim 1 support the proposition that legally-involved persons in substance use treatment show a significant amount of variability in their symptoms at the start of treatment. With this variability being quantifiable using latent profile analysis, the next aim sought to pinpoint client characteristics that increase someone's odds of belonging to one class as compared to another.

To test Aim 2, participants' sociodemographic information and risk-related variables were considered as predictors of profile membership. Based on the Shared Vulnerability Hypothesis (Stewart & Conrod, 2003), the author theorized that persons with more shared risk factors for substance use and post-traumatic stress would have an increased probability of belonging to the class with the most severe symptoms (i.e., high substance use, high trauma). There was a consistent pattern of results wherein self-reported psychological distress was the most robust predictor of profile membership. Increases in psychological distress was associated with a higher probability of people belonging to Class 3 (high substance use, high trauma) when compared to Class 1 (high substance use, low trauma), Class 2 (low substance use, high trauma), and Class 4 (low substance use, low high trauma). Furthermore, increases in psychological distress increased the probability of belonging to Classes 1 and 2 when compared to Class 4. Assigned sex at birth was related to an increased probability of belonging to Class 4; people that were assigned male at birth were more likely to be in Class 4 than Class 1. The remaining

predictors in the model (i.e., age, race/ethnicity, physical health, prior arrests) were unrelated to profile membership.

The results associated with Aim 2 are somewhat inconsistent with the Shared Vulnerability Hypothesis; people that were assigned female at birth (Baranyi et al., 2018; Olff et al., 2007) and who had more physical health problems (Lusted et al., 2013; Voon et al., 2017; Keaney et al., 2011) would be expected to have more severe symptomology. While controlling for psychological distress, however, these variables were not related to profile membership. It is possible that the magnitude of the relationship between these risk variables and profile membership was not large enough to be observed when psychological distress was in the model. This interpretation of the data would suggest that while risk variables may be related to a client's predisposition towards developing a certain disorder, as proposed by the Shared Vulnerability Hypothesis, risk for developing a disorder should not be conflated with the manifestation of overt symptoms. Thus, personological and systematic characteristics may provide limited practical information, when compared to current symptoms, about a client's psychosocial functioning at the start of substance use treatment.

Profile membership was examined as a predictor of treatment engagement to determine whether people belonging to different latent profiles responded differently to substance use treatment (Aim 3). At Time 2 (i.e., post-orientation), people in Class 2 (low substance use, high trauma) reported less treatment participation, counselor rapport, and peer support than people in Classes 1 (high substance use, low trauma) and 4 (low substance use, low trauma). People with low substance use, high trauma (Class 2) also had less treatment satisfaction than people with high substance use and low trauma (Class 1). These results contrasted the author's expected findings; people with the most severe symptoms (i.e., Class 3) were expected to report lower

ratings of treatment engagement when compared to the other classes. In support, legally-involved persons with high PTSD symptoms (i.e., more severe symptomatology) reported less homework compliance and task orientation during a 20-week cognitive behavioral intervention (Miles-Mclean et al., 2019). Furthermore, considering people with high substance use, high trauma did not differ from the other classes, it is unlikely that the trauma symptoms themselves were interfering with treatment engagement. Instead, the relatively low engagement among people in Class 2 could be a function of the treatment program not providing services that addressed their treatment needs. Despite this facility serving clients with a history of substance use, people in Class 2 may have not perceived their substance as their primary concern, which decreased their willingness to engage in treatment.

Examining changes in treatment engagement across time showed that Class 2 (low substance use, high trauma) and Class 3 (high substance use, high trauma) generally increased whereas Class 4 decreased. Concerning Classes 2 and 3, these results demonstrate that people with PTSD symptoms do show improvements on certain measures of treatment engagement despite studies reporting that people with PTSD symptoms achieve fewer positive outcomes in substance use treatment (Brown et al., 2003; Hien et al., 2000; Kubiak, 2004; Najavits et al., 2007). These findings do not necessarily contradict these studies in that this study was not able to assess how these changes in engagement were related to post-treatment outcomes. Future studies could consider directly investigating how these changes in engagement are associated with 1) improvements in substance use and PTSD symptoms and 2) overall psychosocial functioning post-treatment. While people in Class 2 showed a significant improvement in measures of treatment participation and peer support, this class also had the lowest ratings of treatment engagement at the start of treatment. These results suggest that people with low substance, and

high trauma may be at risk for low engagement when entering a substance use treatment program. Pending replication, this information could be used to create supplemental programs for people with low engagement at the start of treatment to increase engagement, adherence to the treatment protocol, and treatment effectiveness.

The decrease in treatment engagement for people in Class 4 (low substance use, low trauma) could be the result of these clients, who have low treatment needs, being assigned to a high intensity treatment program. More precisely, clients in Class 4 had relatively high levels of engagement at Time 2 but showed a decrease in engagement at Time 4. This decrease could be because clients in this class had a relatively high level of functioning at intake—as demonstrated by the low substance and low trauma symptoms—and were able to adapt to the demands of treatment. In the long-term, however, this could have been a detriment in that these same clients could have become frustrated or disengaged with the program that is designed for people with higher treatment needs. This explanation would be consistent with the tenets of the Risk-Need-Responsivity model (Bonta & Andrews, 2007), which emphasizes the need for a match between program intensity and client need. As such, people with low need that are assigned to an intensive treatment program may require additional incentives to stay involved with the process of treatment.

In a final analysis, changes in treatment engagement were evaluated as a mediator of the relationship between profile membership and recidivism post-treatment (Aim 4). Profile membership was differentially related to treatment engagement; however, changes in treatment engagement were unrelated to recidivism rates 6 months, 1 year, 2 years, 3 years, or 4 years following treatment. This finding juxtaposes literature showing that treatment engagement is associated with recidivism among legally-involved persons (Goodson et al., 2020; Joe et al.,

2001; Miles-McLean et al., 2019). For example, Yang et al. (2013) found that increases in treatment engagement, measured using the TCU ENG Form used in the current study, was correlated with fewer rearrests in the 12 months following an in-prison substance use treatment program ($r = -0.08$, $R^2 = 0.01$). Given the modest effect size between treatment engagement and recidivism, it is not entirely surprising that measures of treatment engagement were not correlated with rearrests in the current study. Furthermore, since static (e.g., age, assigned sex, criminal history) and systematic risk factors (e.g., employment problems, low income) are such robust predictors of recidivism (Eisenberg et al., 2019; Goodley et al., 2022; Yukhnenko et al., 2020), on a practical level treatment engagement may not be the most meaningful predictor of recidivism for legally-involved persons.

The absence of a mediational effect in the current study does not suggest, however, that profile membership is entirely unrelated to clients' success in substance use treatment. Rather, the author would propose that profile membership may be specifically related to clients' short-term success in treatment rather than their long-term success. Since profile membership was related to treatment engagement, and treatment engagement is considered a precursor to therapeutic change (Simpson, 2004), changes in engagement may be strictly related to more immediate outcomes in substance use treatment (such as improvements in quality of life, psychosocial functioning, motivation for change). Indeed, treatment engagement has been correlated with improved motivation for change (Simpson et al., 2012) and meaning in life (Sease et al., 2023) in legal samples. As such, forthcoming studies should consider how the differential association between profile membership and treatment engagement affects these variables, which in turn affects clients' capacity to adjust to the difficulties associated with reentry. Such studies could approach these research questions through a recovery capital-based

paradigm (see Best & Hennessy, 2021; Cloud & Granfield, 2008; Hennessy, 2017), using measures of psychosocial functioning as a primary outcome variable. Within this framework, studies may be able to provide a more detailed account as to which short-term outcomes are most likely to be affected by comorbid substance use and PTSD.

Future Directions and Limitations

The present study has limitations that should be considered when interpreting the practical implications of these results. This study was correlational; participants were not randomly assigned to latent classes and therefore the relationships reported in the present study are not causal. Additionally, latent profile analysis was used to create classes of people who shared similar substance use and post-traumatic stress symptomology. Although a useful approach for quantifying distinct patterns of responding to self-report measures, statistically-driven approaches, such as latent profile analysis, suffer in that the model that best fits the data may not necessarily be the most conceptually and practically meaningful solution (see Spurk et al., 2020). This limitation creates a degree of ambiguity when interpreting the results, which can be biased based on a researcher's a priori assumptions about the data. Another limitation that could limit this study's generalizability is that the results from this study may not be representative of all legally-involved persons. For example, it is possible that the four-factor solution obtained in this study does not correspond to the clinical presentation of legally-involved persons at different facilities or levels of supervision (e.g., probation, parole). On one hand, this is a limitation insofar as correctional agencies may not be able to directly apply these findings to their facility; on the other hand, this study provides a unique opportunity for agencies to use their own facility's data to create protocols that redress the healthcare concerns of the populations they generally serve. The latter of these implications could help facilities reduce the

economic burden of treatment services while simultaneously moving towards more individualized treatment protocols. Programs or curricula that address the needs of the sample can be retained and those that do not can be eliminated from the programming altogether.

This study used measures of substance use and post-traumatic stress as indicators defining profile membership. This approach was taken to maximize the clinical implications this study would have for in-prison treatment programs. Said another way, the author assumed that by focusing exclusively on substance use and post-traumatic stress, the resultant solution would provide a parsimonious depiction of common clinical presentations among legally-involved persons. This approach fails, however, to account for other psychiatric symptoms (e.g., anxiety, depression, suicidality) that commonly covary with substance use and post-traumatic stress (Facer-Irwin et al., 2019; Lai et al., 2015; Panagioti et al., 2012). Thus, the exclusion of additional psychiatric symptoms that affect people in substance use treatment could have resulted in an oversimplified solution. Future studies are needed to identify those symptoms most likely to affect people in substance use treatment and incorporate them alongside substance use and post-traumatic stress when creating latent profiles. These studies should closely consider the need for latent profiles that accurately capture clients' clinical symptoms while also attempting to reduce the noise that comes from the inclusion of variables that lack practical significance or conceptually overlap with other variables in the model (e.g., hyperarousal and anxiety).

The resultant four-class model showed that there was a considerable amount of variation between substance use and post-traumatic stress; the model was able to classify people into one of four classes with a reasonable amount of certainty. There was not, however, a significant amount of variation among the measures of substance use and post-traumatic stress. These results would suggest that it may not have been necessary to separate substance use and post-

traumatic stress into subscales based on their individual symptoms. Furthermore, considering the high associations among the indicators of substance use and PTSD, the globality of these measures could have masked the variability observed between the latent profiles (see Morin & Marsh, 2015 for additional information on this topic). Forthcoming investigations may consider using composite scores for these constructs and include additional measures unrelated to substance use and PTSD that aid in the categorization of people participating in an in-prison treatment program. It will be important, however, to replicate these results using an updated measure for PTSD considering the current study used the TCU TRMAForm—a validated screener created based on DSM-IV. Thus, the inclusion of negative alterations in mood or affect could necessitate retaining the separation of post-traumatic stress into its symptom categories.

Researchers and policymakers have discussed at length the pros and cons of using recidivism as an outcome variable in applied research (see Harris et al., 2009; Johnson, 2017; Ruggero et al., 2015) and the current study suffers from the limitations of this approach. Recidivism was defined as a dichotomous variable indicating whether a participant was rearrested in the four years post-treatment (Yes vs. No) and as a continuous variable representing the number of days to first rearrest. The primary limitation to this approach is that deaths that occurred during the follow-up period were not accounted for. This could have resulted in the rearrest rates reported in the current sample being lower than the true rearrest rates for the sample. Furthermore, rearrests should not be conflated with, and do not provide insight into, reconvictions or reincarcerations. This distinction suggests that people in the current study that were rearrested were not necessarily guilty of a crime. Lastly, recidivism is generally used as a proxy for program effectiveness following a period of legal system involvement. This is inherently limited in that not recidivating is not synonymous with an absence of criminal

behavior. Lack of future involvement with the legal system, although a reasonable outcome for legal facilities and policymakers, does not provide information about a person's (un)successful transition back into the community following involvement with the legal system.

Conclusion

In summation, this study investigated the impact of substance use and post-traumatic stress on clients' success in substance use treatment. Participants were classified into four classes: 1) high substance use, low trauma; 2) low substance use, high trauma; 3) high substance use, high trauma; and 4) low substance use, low trauma. Psychological distress at baseline was the primary predictor of group classification, with increases in psychological distress increasing the probability of belonging to every class except the low substance use, low trauma class. People with low substance use and high trauma (Class 2) had the lowest ratings of treatment engagement at the start of treatment. Additionally, Classes 2 and 3 showed positive changes in engagement during treatment whereas people in Class 4 experienced a decrease in treatment engagement. Changes in treatment engagement were unrelated to rearrests in the four years following treatment. This study provides an empirical foundation for succeeding investigations interested in the interaction between substance use and post-traumatic stress and how concurrent symptomology may affect legally-involved persons in substance use treatment.

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ABSTRACT

A LATENT PROFILE ANALYSIS OF SUBSTANCE USE AND POST-TRAUMATIC STRESS ON SUBSTANCE USE TREATMENT OUTCOMES AMONG PEOPLE INVOLVED WITH THE JUSTICE SYSTEM

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The present study used a person-centered analysis to classify legally-involved persons in substance use treatment into mutually exclusive groups based on their clinical presentation of substance use and post-traumatic stress. Predictors of group membership were tested, and group classification was evaluated as a predictor of progress in substance use treatment, defined using participants' self-reported treatment engagement. Rearrest rates in the 4 years following treatment were evaluated as a function of group membership. The results showed that there was a significant amount of variability in participants' substance use and post-traumatic stress symptomology at the start of treatment. Psychological distress was the primary predictor of group classification and profile membership was differentially related to participants' self-reported treatment engagement. Changes in treatment engagement did not mediate the relationship between profile membership and recidivism in the 4 years following treatment. These results can be used to inform screening tools, assessment protocols, and adaptive treatment models to better serve people involved with the legal system experiencing comorbid difficulties with substance use and post-traumatic stress.