UNDERSTANDING SUBSTANCE USE TRAJECTORIES AMONG PROBATIONERS AND THE IMPACT ON RE-ARREST

by

Jennifer Lerch
A Dissertation
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The Requirements for the Degree
of
Doctor of Philosophy
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DEDICATION

This dissertation is dedicated to Melissa and Andre. Thank you for always having my back and all your love and support through everything.

To Steph Maass, for always being there for me. I would not have made it through this process without your support during every up and down.

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ABSTRACT

UNDERSTANDING SUBSTANCE USE TRAJECTORIES AMONG PROBATIONERS AND THE IMPACT ON RE-ARREST

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More than 20 million individuals have a substance use disorder in the United States. Individuals cycling in and out of the criminal justice system disproportionately experience substance use disorders that result in a multitude of negative outcomes. Prior research demonstrates that substance users are heterogeneous in their patterns of use, and individual characteristics such as age, type of drug use, prior treatment experiences, and criminal history predict patterns of use. While there is a growing body of research examining substance use patterns and trajectories, there are still large gaps in our knowledge, particularly among probationers. The current study examines the substance use patterns among individuals while on community supervision, with attention to the factors that predict membership into those substance use groups and how those substance use groups may predict re-arrest. Six groups of substance users emerged from the data: abstainers, late-increasing, low-moderate, increasing, decreasing, and high user groups.

The number of probation contacts, formal treatment attendance, number of arrests, and housing in a non-controlled environment were the time-varying predictors related to group membership, while risk-taking, family and peer drug use, initiating substance use under the age of 16, and severity of drug disorder were time-stable risk factors for group membership. Despite the distinct substance use patterns that emerged, the pattern of substance use did not predict later re-arrest among this group of individuals on community supervision.

CHAPTER ONE: INTRODUCTION

> *"I've been using drugs for a while but there have been like periods in my life when I've stopped… I was locked up for 3 years and then I was on probation for 3 years so that was like 6 years when I wasn't do nothing at all…I've been stopped quite a few times that's just on cold turkey, yeah I have done got to the point when I'm using heroin every day and I'm still out there trying to sell the drugs and it was just a day popped up when I was just saying hey this ain't for me no more…You know when I had stopped that time for like over a year I stopped." (44-year-old male)*

Just like this person, there are millions of Americans across the United States struggling daily with substance use. These individuals face substance use challenges in cycles, often many times throughout their lifetime. According to the 2018 National Survey on Drug Use and Health, approximately 20.3 million individuals 12 and older in the United States have a substance use disorder[1] for illicit drugs, alcohol, or various combinations (Substance Abuse and Mental Health Services Administration (SAMHSA), 2019). The financial cost to society is in the billions of dollars, ranging from $200 billion (Office of National Drug Control Policy (ONDCP), 2014) to more than $442 billion when considering illicit drugs and alcohol abuse (National Institute of Drug Abuse (NIDA), 2020). These costs accrue from such factors as loss of employment, health care, criminality, incarceration, and law enforcement. Beyond these larger societal costs, there

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[1] This report refers to substance abuse and dependence as defined by the DSM-IV (Diagnostic and Statistical Manual of Mental Disorders, 4th edition); however, the DSM-V (Diagnostic and Statistical Manual of Mental Disorders, 5th edition) combines these into one term referred to as substance use disorders (Hasin et al., 2013).

are the individual costs associated with substance use such as loss of social support and family/friend relationships, severe health problems, legal problems, and death (ONDCP, 2014). Creating policy and practice to overcome these consequences of substance use suggests a crucial need to understand the patterns of substance use and the associated outcomes.

While substance use continues to be a challenge overall, individuals cycling in and out of the criminal justice system disproportionately experience substance use disorders that result in a multitude of negative outcomes. In 2016, probation or parole (i.e., community supervision) supervised seven out of 10 adults under correctional control in the United States (Kaeble & Cowhig, 2018). Probationers are consistently at least two times more at risk of having substance use disorders across different substances as compared to non-probationers (Fearn et al., 2016). For more than a decade, the number of individuals on probation and their risk of having substance use disorders remained relatively stable (Fearn et al., 2016; Feucht & Gfroerer, 2011; Glaze & Kaeble, 2014) despite one of the primary tenants of community supervision being to cease substance use. While there is a growing body of research examining substance use patterns and trajectories, there are still large gaps in our knowledge, particularly among probationers.

Prior research demonstrates that substance users are heterogeneous in their patterns of use, both within a single type of substance and across different types of substances (Chou et al., 2003; Hser et al., 2008; Hser, Huang, et al., 2007; Hser, Longshore, et al., 2007; Kertesz et al., 2012; Teesson et al., 2017). Most recently, researchers found that heterogeneous patterns of use also exist among probationers during active supervision (Caudy et al., 2014). Additionally, there are individual characteristics that predict membership in these substance use trajectories such as age, a hard drug user, history of trauma, prior treatment experiences, employment, criminal history, age of substance initiation, history of overdose, and mental health issues (Caudy et al., 2014; Harrison et al., 1997; Hser et al., 2008; Hser, Huang, et al., 2007; Teesson et al., 2017). However, researchers know very little about how these use patterns predict outcomes, especially criminal justice outcomes. Teesson and colleagues (2017) found that those who do not decrease their use had the worse substance use, health, and criminal justice outcomes. Additionally, Caudy and colleagues (2014) found evidence that trajectories of substance use predicted later treatment outcomes, but did not examine the impact on criminal justice outcomes such as re-arrest. We know individuals using substances are more likely to experience negative criminal justice outcomes (Bennett et al., 2008; Green et al., 2019; Huebner & Cobbina, 2007; Lennings et al., 2003; MacKenzie et al., 1999), but it is unclear how different patterns of use may predict re-arrest during community supervision.

This dissertation addresses two large gaps in the existing research. First, this project expands our limited knowledge about substance use trajectories during probation. Research to this point reveals that most substance users go through multiple cycles of use, recovery, and relapse throughout their lifetime (Best et al., 2017; Prochaska et al., 1992). However, researchers are only beginning to explore, in more depth, the heterogeneous cycles and patterns of use that various individuals experience throughout their lifetime, including during particular times in their lives, such as throughout community supervision, which may reveal different patterns (Hser, Longshore, et al., 2007). The criminal justice system bans most individuals from any illicit substance use and many times alcohol use as well while under community supervision. Very few studies examine what substance use patterns look like for individuals while on probation (Caudy et al., 2014, MacKenzie et al., 1999; MacKenzie & De Li, 2002). This study builds on this limited research to examine potential substance use trajectories of probationers during community supervision.

Second, this research examines how various trajectories of substance use predict re-arrest. While modeling techniques such as group-based trajectories allow for significant advances in understanding patterns of behavior, critics suggest that researchers using these techniques have not taken the necessary step of testing the ability of groups to predict later behavior (Kreuter & Muthen, 2008). These critics posit that without the ability to predict later behavior, creating groups of behaviors (e.g., substance users) is a wasted endeavor, including a lack of theoretical significance. Presently, only one study takes this next step with probationers, but it is limited to examining treatment behavior (Caudy et al., 2014). The current study examines the extent to which probationer's trajectories of substance use predicts re-arrest.

Beyond the scholarly significance of this work, this research provides information necessary to guide both policy and practice regarding how the criminal justice system, particularly community supervision, handles substance users. Community supervision agencies struggle with the ability to distinguish between those who most need access to limited resources versus those for whom probation is enough to stop their substance use.

Beyond knowing that some probationers will continue to use while on supervision and that substance use increases the probationers' chances of failure, community supervision agencies have very little understanding regarding how to *proactively* identify which substance users are at the greatest risk of failure. *This research provides insight to agencies regarding both what probationers substance-using patterns look like during community supervision and what characteristics distinguish the different use patterns.* Additionally, *the potential impact of these patterns on re-arrest provides guidance to agencies about what substance using profiles need the greatest attention* (e.g., more intensive treatment) to prevent probation failures.

To address these gaps in knowledge and need of the field, this dissertation addresses the following three research questions: *1) What are the patterns of substance use among individuals while on community supervision?; 2) Which factors predict group membership in the substance use trajectories?, and, 3) Do the substance use trajectories predict re-arrest and/or time until re-arrest?.*

CHAPTER TWO: LITERATURE REVIEW

Both the theoretical and empirical understanding of the relationship between community supervision and substance use are exceptionally limited. Much of the available theory and knowledge discusses general substance use and/or criminal behavior without paying attention to the active criminal justice status of the individual (e.g., probation). This literature review draws from the theoretical underpinnings of desistance and empirical studies regarding substance use, criminal justice outcomes, and trajectories of substance use.

Community Supervision and Desistance

Guided by life course theory, researchers of multiple disciplines have long sought to understand the pathways and trajectories that individual's lives take. Life course theory focuses on the developmental interplay between individual's lives and social, continuously changing conditions they exist within (Elder, 1994). A large portion of life course theory focuses on how age interplays with different behaviors throughout the life span and particularly focuses on how childhood experiences impact later life trajectories. A growing body of research in criminology and substance use looks beyond childhood development to the interplay of adulthood experiences and behavior. One stream of inquiry emerging from life course theory is the concept of desistance (Best et al., 2017; Laub & Sampson, 2001).

Desistance is generally defined as "a process- not an event- in which criminal activity decreases, and reintegration into the community increases, over time" (Rosenfeld et al., 2008, p. 86). Desistance is defined not as the outcome, but the process to achieve the outcome of stopping a behavior (Laub & Sampson, 2001). Researchers examining criminal behavior take different stances on the most significant factors contributing to desistance (Best et al., 2017). The research of Laub and Sampson (1993; 2001) focuses largely on social bonds and the role that both informal and formal bonds and control play in altering criminal pathways taken by individuals from adolescence through adulthood. Other researchers posit that internal factors such as identify, self-efficacy, and impulsiveness are the most important factors in the path of desistance (Bushway & Paternoster, 2013; LaBel et al., 2008; Maruna, 2001; Miner, 2002).

The concept of desistance overlaps significantly with the concept of recovery in substance use research (Best et al., 2017). Best and colleagues (2017) discuss how both desistance and recovery focus on the importance of identity and social capital, as well as how each display distinct stages in their process. Additionally, the extreme stigma toward individuals with substance use and criminal histories mirror one another (Best et al., 2017). Just as in criminal desistance studies, researchers exploring patterns of substance use have been challenged in determining the factors most important to predicting substance use desistance. Hser, Longshore, and Anglin (2007) suggest that individual's heterogeneous patterns of substance use can be explained by understanding various experiences individual's go through in their life. For instance, they suggest that exposure to various treatment experiences and service agencies could potentially create turning points for substance users to change their behavior patterns. In a review of 39 qualitative and mixed methods studies, O'Donnell and colleagues (2018) found that different individual, social, and environmental factors were associated with different phases of substance use. Furthermore, in discussing substance use and criminal pathways it is common for each to play a part in the others process.

Left largely unexplored in both research on desistance from criminal behavior and substance use is what patterns of substance use look like on community supervision and the ultimate impact on later criminal justice outcomes. Community supervision occurs in many forms including probation, pretrial release, and parole. The various forms of supervision all attempt to monitor, control, and change individual behavior in a manner that is acceptable to society and ultimately promotes desistance from negative behaviors (Weaver, 2013). Given that a large proportion of individuals under community supervision exhibit substance use problems (Freucht & Gfoerer, 2011), a common behavior change that supervision targets is substance use. Due to the monitoring and responses of community supervision, the time that an individual is under community supervision may reveal unique patterns of substance use that could help identify opportunities to intervene and promote long-term desistance, especially if these substance use patterns are related to later recidivism outcomes. However, there is very little research exploring individuals' substance use patterns while on community supervision. Most available research only limitedly explores a connection between criminal behavior and substance use independent of use patterns while under a specific criminal justice status. The current study begins to take a look at how individual substance use patterns look during community supervision and how those various trajectories later predict re-arrest and the time to re-arrest while on supervision. This research is a springboard to better understand how community supervision may intercede in changing individuals' substance using behaviors.

Community Supervision, Substance Use, and Criminal Behavior

Prior research demonstrates a strong connection between criminal behavior and substance use. In particular, those involved in the criminal justice system are more likely to experience negative outcomes if they continue their substance use (Marlow, 2011). Despite the many programs and techniques created and/or used by criminal justice agencies to stop substance use, failing drug testing is one of the most common violations committed during community supervision (Gray et al., 2001). Furthermore, these programs and techniques produce mixed results at best. For instance, one common mechanism of addressing substance use for those under community supervision is through drug testing or other monitoring mechanisms. Despite wide use, one systematic review found no evidence that using only monitoring or control techniques as a form of substance abuse treatment through community supervision reduced recidivism (Chanhatasilpa et al., 2000). However, other research supports techniques such as drug testing, when used in a setting of swift and certain sanctioning. Grommon, Cox, Davidson, and Bynum (2013) conducted a randomized controlled trial to test the impact that drug testing had on parolee recidivism. The frequency of drug testing as well as the timing of receiving results and the swiftness of the consequences for those results varied per study arm. They found that "exposure to frequent, random testing and certain and swift consequences significantly lower relapse and recidivism rates during the process of transition into the community" (Grommon et al., 2013, p. 162). However, the results diminished after the study protocol increasing the swiftness and certainty of consequences ended. These findings support other programs such as Project HOPE that found success with drug tests by using swift and certain sanctioning coupled with intensive treatment (Harrell & Roman, 2001; Hawken & Kleiman, 2009). Some of the inconsistent findings for control techniques may be due to the inattention to balance between control behaviors and positive reinforcements. For instance, Schwalbe (2019) found that when probation officers work with youth, there needed to be more positive pressures (incentives) and fewer negative pressures (sanctions), but that both must be present to effectively impact substance use behavior.

Even treatment provision as a method of stopping and preventing substance use on probation has limited positive findings. In a meta-analysis examining interventions aimed at reducing or stopping substance use among individuals involved in the criminal justice system, Perry and colleagues (2009) only found 24 studies that at least had a randomized control group. Most of the studies were methodologically weak and did not provide enough of an effect to demonstrate effectiveness; only therapeutic communities demonstrated effectiveness (Perry et al., 2009). This work supports previous findings that programming aimed at reducing offending through addressing substance use demonstrates sometimes promising, but often limited effectiveness (MacKenzie, 2001). The limited and mixed findings for the current methods in place to stop substance use on probation demonstrate the need to better understand substance use trajectories of those on community supervision and examine how those patterns impact later behavior. A better understanding of substance use trajectories may lead to better application of these techniques to create substantial change for probationers with substance use issues.

The limited available research supports how differing types of substance use and behavior lead to different outcomes, even among those on community supervision. Bennett and colleagues (2008) conducted a meta-analysis looking at 30 studies between 1980 and 2003. They found that overall, substance users were 2.8 to 3.8 higher risk of offending behavior. The authors found crack users most likely to offend, followed by heroin and cocaine users respectively. They also found a relationship between offending behavior and marijuana use, but that it was much weaker than the relationship of the harder drugs. Although weaker than the relationship between serious drug use and offending, recreational use did have a relationship with offending behavior (Bennett et al., 2008). The authors found the relationship between offending behavior and drugs to be stronger among adult populations. Similarly, Lennings et al. (2003) examined youth (age 12-22) in detention centers in New South Wales and found that increased cocaine and alcohol use related to an increase in violent crime.

Examining a sample of felony probationers in Northern Virginia who reported to their agent at least monthly, researchers discovered a number of notable findings regarding substance use and criminal behavior at the beginning of supervision. They found that substance use (both heavy drinking and illicit drugs), criminal activities, and gun ownership declined during supervision, but did not stop for everyone (MacKenzie et al., 1999; MacKenzie & De Li, 2002). Social bonds did not change and actually served as a protective factor against nondrug continued criminal behavior (De Li et al., 2000; MacKenzie & De Li, 2002). Arrest in particular affected criminal involvement and substance use; however, probation seemed to keep these at a lower level. Increased criminal behavior was committed when individuals used substances, particularly property crimes, and probation had the largest effect on changing behavior among older individuals (De Li et al., 2000; MacKenzie et al., 1999). Substance use increased the likelihood of nondrug crimes (De Li et al., 2000; MacKenzie & De Li, 2002). The results also demonstrated that having a spouse protected against criminal involvement and criminal lifestyle (i.e., gun ownership) increased risk for these probationers (De Li et al., 2000).

Further research provides some insight into how substance use among probation samples relates to recidivism measures. Degiorgio and DiDonato (2014) examined a dataset of adult probationers using the SAQ-Adult Probation III risk assessment tool to predict probation revocations. They found that more arrests, felony arrests, number of times in prison, and a history of drug and alcohol use was predictive of increased revocations (Degiorgio & DiDonato, 2014). Webster and colleagues (2010) examined a sample of rural felony probationers to determine if violent and nonviolent probationers behaved similarly. They found that violent probationers were more likely to be men, older, commit more criminal activity, report more lifetime drug use, and mental health issues.

Olson & Lurigio (2000) examined data collected on adult probationers in Illinois in 1997. They found that probationers who were younger, had a lower income, resided in an urban environment, had a more extensive criminal history, and drug abuse/dependence history were more likely to have a new arrest, technical violation, or revocation. Individuals with a lower education were more likely to be revoked or be newly arrested. Minorities had a greater likelihood of receiving a technical violation or being re-arrested. Drug or property offenders were more likely to receive a technical violation (Olson & Lurigio, 2000). Probationers' substance use history was a greater predictor of outcomes than their conviction history. Huebner and Cobbina (2007) examined probationers discharged in Illinois in November 2000 and found drug-using probationers were more likely to be re-arrested and to fail more quickly. Additionally, the authors found that those who were younger, male, had a more severe criminal history, lived in an urban area, black, or unemployed were more likely to recidivate. Chamberlain and colleagues (2019) found that among parolees, factors such as being male, parole status, time between release and first medical appointment, drug use disorders, and living with family/friends were risk factors for continued use on supervision.

These studies not only show that substance use plays a significant role in understanding further criminal involvement among probationers, but also how nuanced and interconnected substance use may be to other characteristics. There is a great need to understand to what extent substance users consist of groups, some of which may portray specific characteristics (e.g., age, race, gender) and if those groups then predict recidivism in a meaningful manner.

Trajectories of Substance Use

Limited research examines trajectories of substance use overall and even less exists that focuses specifically on a criminal justice population. However, a few notable contributions in the literature provide a foundation for this research. In an early study looking at differing patterns of use from adolescence to young adulthood, Kandel & Logan (1984) found that individuals using alcohol or tobacco stabilized their use around the age of 18, while marijuana users stabilized around the age of 19 and then decreased used by age 23. They found that males tended to use more and increase at a faster rate than female students.

Chou and colleagues (2003) examined a group of cocaine users in Los Angeles using face-to-face interview data with a 36-month follow-up. The researchers recruited these participants from clinics, emergency rooms, and jails. Using the Natural History Instrument to examine individuals' lives (e.g., events and substance use), the researchers found that different patterns of decreased use depended upon the type of treatment, if any, the cocaine users received. The authors found that the no treatment group maintained continued use, the group treated specifically for cocaine addiction declined rapidly, but then drastically increased use, and the group treated for drug use (non-specific to cocaine use) also decreased their use at treatment, but then increased slightly after treatment initiation (Chou et al., 2003). Overall, the researchers found that these cocaine users decreased their use by five times when they were in treatment as compared to not being in treatment; however, there was evidence of the cycle of relapse once treatment was over. Furthermore, they found no evidence that treatment duration affected use after the initial impact of starting treatment (Chou et al., 2003).

A group of researchers from the UCLA Integrated Substance Abuse Programs (ISAP) are at the forefront of research examining trajectories of substance use. In one notable study from this group, Hser, Huang, et al. (2007) used growth mixture modeling techniques to explore trajectory patterns of use among a sample of 471 male heroin users in the California Civil Addict Program in 1964-1965. Examining self-reported heroin use (i.e., “mean number of days per month using heroin each year over 16 years since onset of heroin use”), they identified three trajectory groups: stably high, late decelerators, and quitters (Hser, Huang, et al., 2007, p. 551). The late decelerators maintained high use, but then later decreased into nonuse. Over the 16 years of follow-up, the authors found that the stably high users were less likely to be employed, had fewer years of continuous abstinence, and more alcohol dependence. The early quitters had fewer mental health issues, initiated substance use at an older age, and spent less time incarcerated. The late decelerators had the highest mortality rate.

Hser and colleagues (2008) compared the trajectories of drug use between cocaine, methamphetamine, and heroin users using data collected from five studies conducted in California. These five studies used the Natural History Instrument from pooled and recruited clients from emergency rooms, clinics, and jails (n=1797). Using growth mixture modeling, they found five trajectories of use: high use, moderate use, low use, decreasing use, and increasing use. They found that heroin users were more likely to fall into a high using group as compared to cocaine and methamphetamine users who were more likely to be in the moderately using group. Overall, individuals who fell into the high using trajectory group were younger when both their drug use and criminal history started, spent more time incarcerated, less time employed, and many had experienced substance abuse treatment for the first time during a prison stay.

Recently, Teesson and colleagues (2017) examined trajectories of heroin use among individuals who participated in the Australian Treatment Outcome Study. This sample consisted of individuals recruited from randomly selected agencies treating heroin dependency around Sydney (n=428). Using group-based trajectory modeling, they found six groups of users: no decrease, gradual decrease, gradual decrease to almost abstinence, rapid decrease with late increase (relapse), rapid decrease with rapid increase (relapse), and rapid decrease to abstinence. They found very few variables predicting group membership. Only being over 30, prison history, history of overdose, first using heroin before 17 years of age, and severe mental health disability predicted group memberships. However, they did find the trajectories to be related to several outcome variables at the 10 to 11 year follow-up, including time in prison since baseline, recent criminal involvement and substance use, intravenous related health problems, current treatment, stable housing, heroin dependence, and financial wages. Overall, the worse outcomes were associated with no decrease in use.

One study examined probationers with a substance abuse condition in a large urban environment. Caudy and colleagues (2014), using semi-parametric group-based mixture modeling, found different patterns of drug use among probationers. The five groups that emerged were abstainers (averaged less than two drug use days per 90 days

FU), low-rate stable users (averaged 10.5 drug use days), rapidly declining users (use dropped quickly after baseline), gradually declining users (increase and then gradual reduction), and high-rate stable users (high rate of use entire time). Numerous baseline characteristics predicted membership to these trajectories of use. For instance, the rapidly declining users were more likely to have higher scores of treatment readiness, and being a hard drug user at baseline was a predictor of continued substance use (i.e., being in any of the four substance using groups as compared to the abstainers) (Caudy et al., 2014).

The Caudy and colleagues (2014) study is one of the first to examine how drug use trajectories predict future behavior. They examined how these trajectory groups predicted treatment outcomes for these probationers and found that the groups predicted different treatment outcomes (Caudy et al., 2014). The rapidly declining group was most likely to attend inpatient treatment, however in comparison to the gradually declining group, the rapidly declining group averaged significantly fewer days attending inpatient treatment. In comparison to the high-rate stable group, the rapidly declining group spent significantly more days in outpatient treatment (Caudy et al, 2014). The findings of this study not only further previous research demonstrating that a probation specific sample also differ in their substance use patterns, even when legally mandated not to use and attend treatment, but that these use patterns can help predict later treatment patterns. This recent research is a significant first step to filling in a gap in understanding substance use among probationers and how substance use patterns affect later outcomes. However, there remains the question of how such patterns of use impact criminal justice outcomes beyond treatment participation.

The limited available research tends to focus on trajectories of use within a single or small numbers of substances, examines non-criminal justice specific populations, and does not examine how trajectories of use influence individual criminal justice outcomes.

CHAPTER THREE: BACKGROUND

Motivational Assistance Program to Initiate Treatment (MAPIT), the parent study from which the data for the current study comes, was a multi-site, randomized controlled trial conducted in Baltimore, MD and Dallas, TX. MAPIT primarily examined the impact that a computerized motivational program (MAPIT) and in-person motivational interviewing (MI) compared to standard probation services (SAU) had on treatment initiation and substance use. Participants eligible for the study were newly on probation (i.e., within 30 days of screening), over 18 years old, competent to be consented, used any illicit substance or significant alcohol (i.e., >= five drinks in a day for men and >=four drinks in a day for women) in the 90 days prior to randomization, and spoke English.

Study Design

MAPIT measured participant characteristics at baseline, two-months, and six-months post-baseline. As shown in Figure 1, after completing the baseline interview, 360 individuals (200 in Dallas and 160 in Baltimore) were randomized to one of three conditions: MAPIT, MI, or SAU. The study used a blocked-stratified randomization (Kernan et al., 1999). Stratification was on the individual's likelihood of further involvement in the justice system, or criminal justice risk (i.e., low/moderate risk or high risk), based on a brief risk screener (seven questions described in the methodology chapter). All individuals received identical management in their respective probation system. Individuals had to complete the baseline interview before the computer automatically randomized them to a study condition. After the baseline interview, if randomized to MAPIT or MI, individuals completed session one, as appropriate, immediately and session two approximately three to four weeks later. Participants completed phone interviews at the two-month follow-up and in-person interviews at the six-month follow-up.

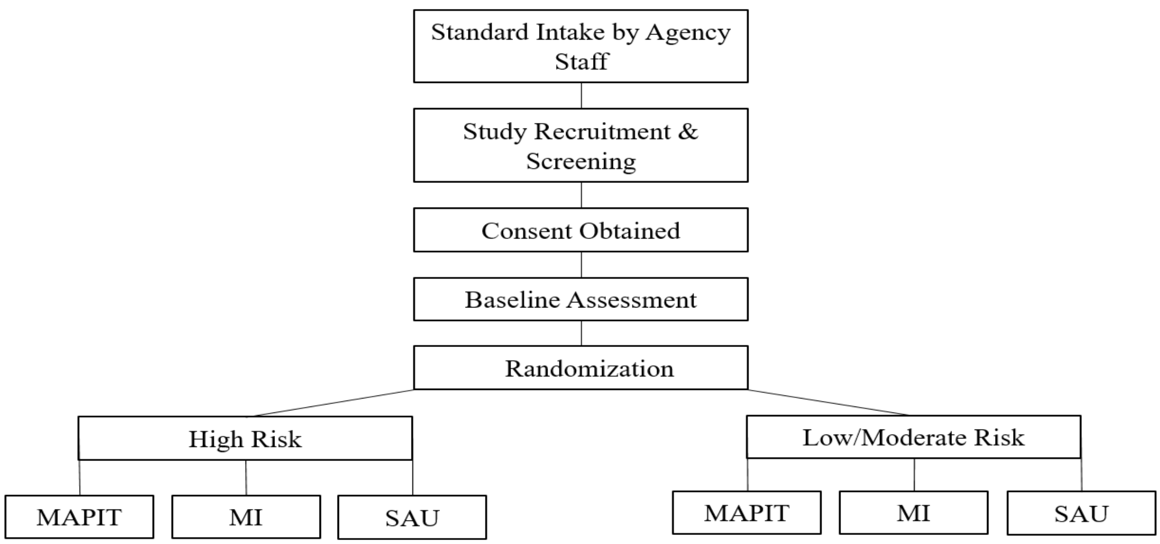


Figure 1: MAPIT Study Design in Dallas and Baltimore

Recruitment, Screening, and Study Flow

Recruitment for the study began in January 2013 for both sites and ended February 26, 2015 for Dallas and June 10, 2015 for Baltimore (Figure 2). MAPIT participants were recruited using face-to-face contact, word of mouth, probation orientation meetings, and flyers/advertisements. In both Dallas and Baltimore, study staff placed flyers and brochures in probation field offices so that interested persons could call study staff to inquire about the study and be screened for eligibility over the phone. Researchers also advertised on websites such as Facebook. Probation officers and intake staff referred individuals and posted flyers in their work areas. In Baltimore, researchers primarily recruited in the central intake office by approaching waiting individuals and screening them in the waiting area. In Dallas, until March 6, 2014, researchers recruited in probation orientation groups, which generally happened before the first probation officer meeting. After March 6, 2014, researchers received a weekly list of new probationers and called individuals to conduct screening phone calls. A court officer gave these individuals an introductory letter about the study and brochure before they were called by the researchers. The recruitment change in Dallas resulted from agency policy changes regarding orientation groups. Within the Dallas sample, researchers recruited 131 participants before the change and 69 afterward. Bivariate analysis examining sample characteristics before and after the recruitment change suggests that this change should not influence the current studies' results (see Appendix A). The sample before and after only differed on one factor, criminal justice risk score. The sample collected after the recruitment change had a significantly higher risk level ($F(1, 166)=5.93$, $p=0.16$). This significant difference is likely due to the risk level stratification and the focused recruitment toward high-risk individuals in Dallas at the end of the study. In other words, Dallas recruited their target number of low/moderate risk individuals earlier in the study recruitment and became focused on recruiting high-risk individuals to balance the stratification during later recruitment.

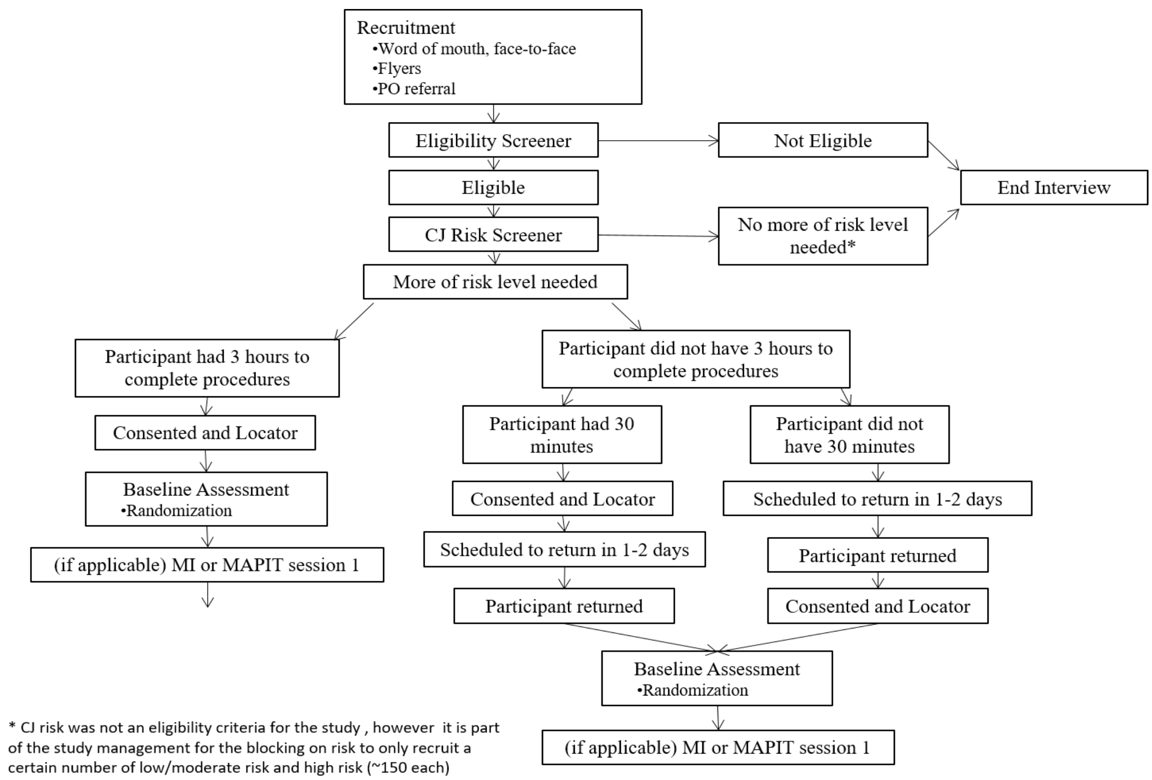


Figure 2: Recruitment and Screening Process

Researchers completed the screening electronically in Discovery to determine eligibility and criminal justice risk level. Discovery, hosted and maintained by DatStat, is an online, study management tool used for managing data collection, automating reminders for interviews, and monitoring study flow (https://www.datstat.com/). Eligible individuals completed the consent form, locator form, and two-hour baseline interview. Randomization occurred automatically within the DatStat Discovery system once the

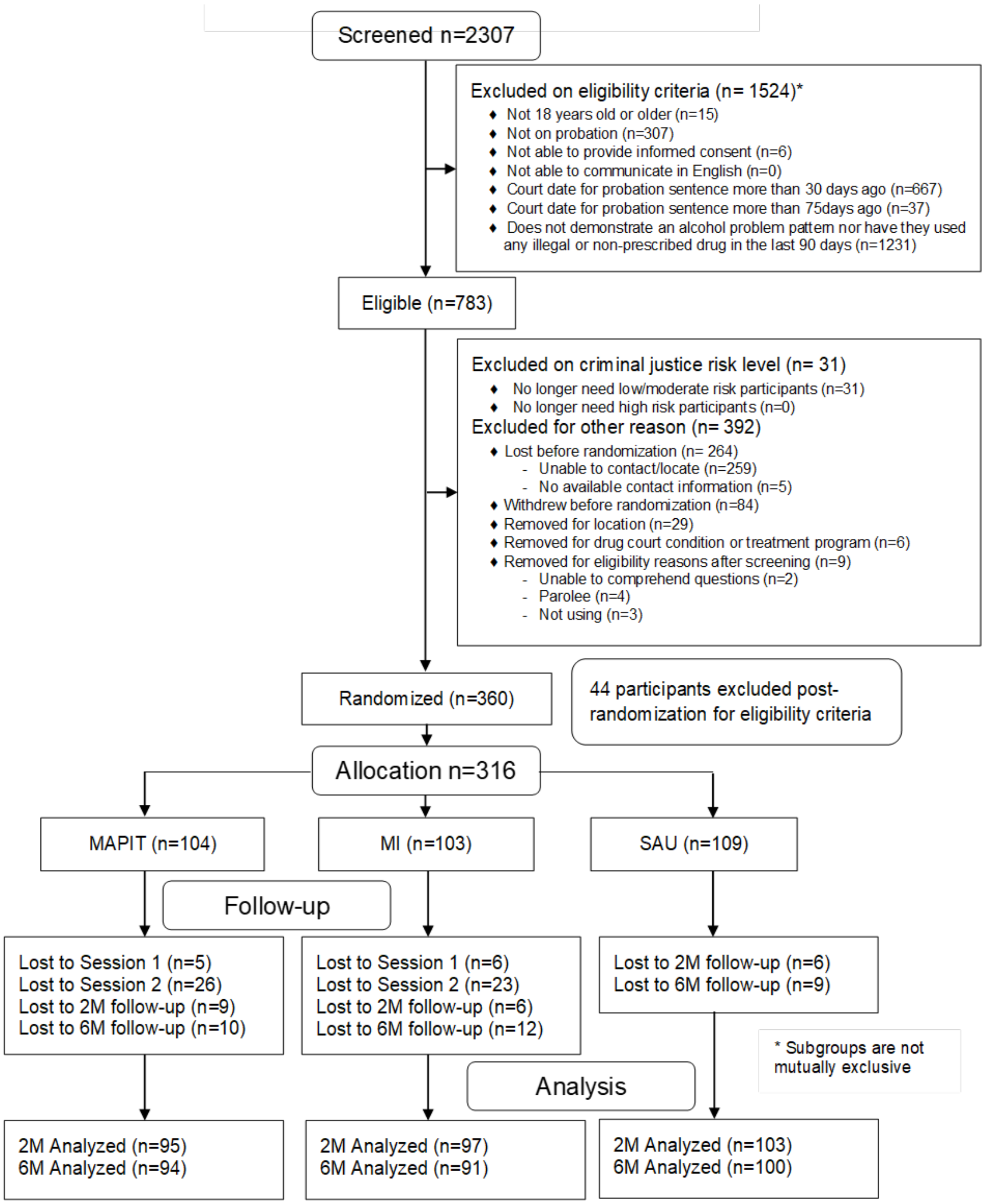


Figure 3: MAPIT Study CONSORT Flow Diagram

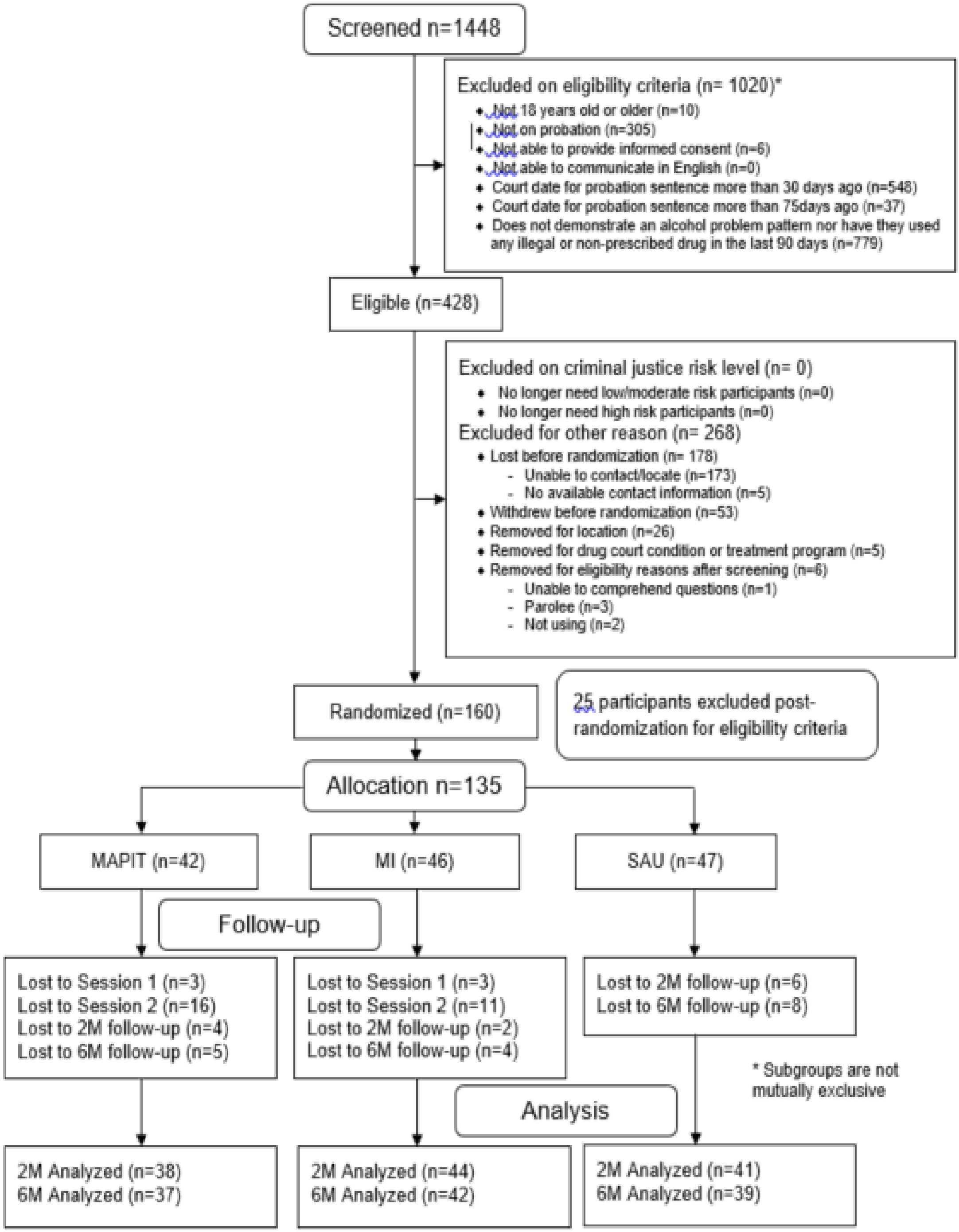


Figure 4: MAPIT Study CONSORT Flow Diagram (Baltimore)

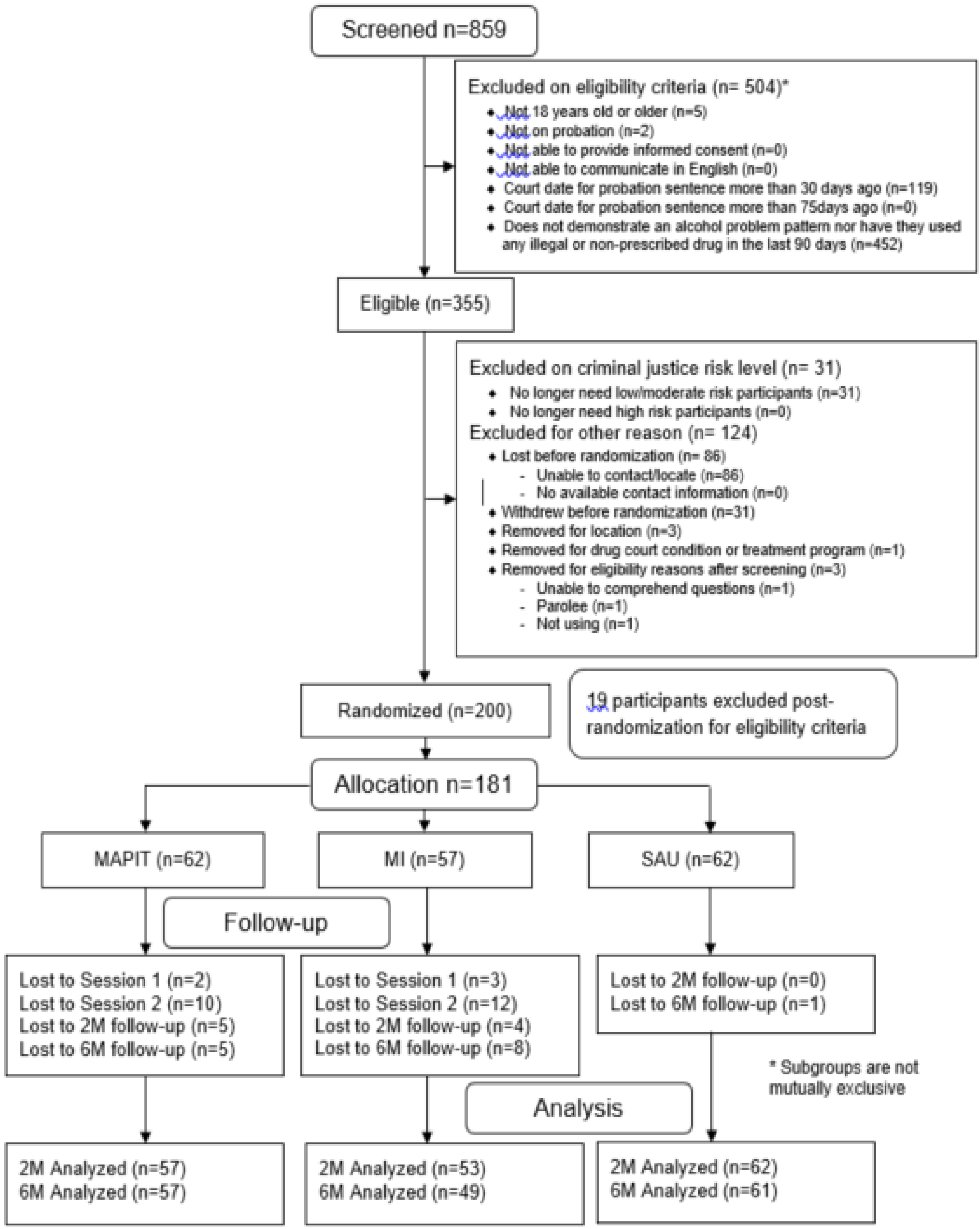


Figure 5: MAPIT Study CONSORT Flow Diagram (Dallas)

researcher submitted the baseline interview. Individuals randomized to either MAPIT or MI completed session one immediately after the baseline interview or scheduled a time to come back for session one within a few days of the baseline interview. After session one, researchers scheduled session two to happen three to four weeks later. All study participants completed a two-month follow-up phone interview and a six-month follow-up in-person interview. Figure 3 shows the study flow for the final study analyses (Cowell et al., 2018; Lerch et al., 2017). Figure 4 and Figure 5 depict the study flow for Baltimore and Dallas separately.

MI and MAPIT Sessions

Researchers developed MAPIT and MI to be comparable programs delivered through different modalities, MAPIT on a computer and MI in-person by a clinically trained counselor. Each session of MAPIT and MI lasted approximately 45 to 60 minutes. In creating the programs, researchers grounded these approaches in extended parallel process to frame risk messages (Witte & Allen, 2000), social cognitive theory through recommendations and comparative information (Bandura, 1986), and motivational interviewing with skills such as open-ended questions and personalized feedback (Miller & Rollnick, 2002). Both programs followed a comparable roadmap through sessions one and two. In session one, the participants were asked about their motivation and commitment level to being successful on probation and in treatment and given feedback based on their reported levels. Individuals received personalized feedback about their criminal justice risk factors, dynamic change factors to reduce recidivism, reported substance use and HIV risk factors, and comparisons of their substance use to others like them. Finally, the participants worked on short-term goal setting activities aimed at probation success. In session two, the goals from session one were reviewed and new short- and long-term goals were identified and set. The participants were again asked about their motivation and commitment level to being successful on probation and in treatment and given feedback based on their reported levels. Their HIV testing recommendation from session one was reviewed and progress discussed. Participants identified social supports within their lives and reviewed how they could ask for help achieving their goals when needed. A personalized printed feedback report was provided for MAPIT and MI participants at the completion of each session. The clinically trained social worker (a member of the research team) conducted both the initial and follow-up in-person sessions with MI participants. The MI program sessions are further described in Spohr et al. (2016) and Walters et al. (2011). The MAPIT program sessions are further described in Walters et al. (2014) and can be viewed at http://youtu.be/9yV6bTn1tVE; http://youtu.be/XEZ5o48WwTg; http://youtu.be/u2SHWG0QXe8; http://youtu.be/wMShVdPpcsw.

Main Findings

In the primary findings from the original study, MAPIT participants increased treatment initiation at the two-month follow-up, as compared to SAU. This significance diminished by the six-month follow-up, but there were differences in the effects. Researchers found no effects on substance use behavior (Lerch et al., 2017). Furthermore, researchers found MAPIT to potentially be a good value compared to MI delivered by a social worker. However, these results were qualified by how treatment initiation was measured (Cowell et al., 2018). The findings supporting MAPIT as a good value held when measuring any treatment initiation (i.e., informal and formal treatment), but did not when using formal treatment initiation only (e.g., group sessions, intensive outpatient) as the outcome.

Further Research Findings

A number of significant findings emerged from the MAPIT research data. Examining the participants reasons for wanting to successfully complete probation during the MAPIT sessions, Spohr et al. (2017) found two factors, tangible loss (i.e., external and currently present focused) and better life (i.e., internal and future focused), related to reasons given by the participants. Better life reasons were significantly, negatively related to the number of substance use days at the two-month follow-up, and significantly, positively related to the number of treatment attendance days. Tangible loss, often a focus of the criminal justice system, was not related to either treatment attendance or substance use. Further examining the MAPIT study arm, Spohr et al. (2015) found that participants who chose to receive text or email goal reminders from the program and who chose more goals had fewer days of substance use at the two-month follow-up and more treatment attendance. These results suggested that the desire for reminders and setting of short-term goals were an early indicator of reducing substance use and improving treatment initiation.

Looking specifically at the MI sessions, Spohr, Taxman, et al. (2016) found that the counselor’s MI spirit (i.e., overall competency with motivational interviewing skills) was related to significantly greater treatment initiation at the two-month follow-up.

However, other fidelity measures were not related to treatment initiation and none of the fidelity measures were related to substance use at the two-month follow-up. In further analyses of the MI sessions, Rodriguez and colleagues (2018) found that when the staff used language inconsistent with MI, the client demonstrated less change talk (i.e., statement expressing desire or commitment to change) and increased substance use at two-months.

Using MAPIT data, researchers demonstrated significant relationships between substance use and other social and health factors. In particular, the quality of social support was related to abstinence, criminal risk level, and sexual risk behavior (Spohr, 2017; Spohr, Suzuki, et al., 2016). While social support was not related to two-month treatment initiation, the likelihood of treatment initiation increased at six-months for those with poorer quality support, who lived with another user, and had more negative interactions (Spohr, 2017). Further analyses found that opiate use and non-opiate illicit drug use was related to chronic pain (Gonzalez et al., 2015). While gender was not found to be directly related to alcohol or illicit drug use among the participants, among men alcohol use was reduced for those who took part in formal treatment (Reingle-Gonzalez et al., 2018).

Researchers found that mental illness among the participants was related to different risk factors. Marshall et al. (2017) found that childhood adverse events had an indirect effect on adult sexual risky behavior through the severity of their mental health symptomology. Furthermore, Rossheim et al. (2018) found that individuals at risk of serious mental illnesses experienced more negative substance use consequences and that alcohol use interacted with these negative consequences. On the other hand, opiate use interacted with negative consequences among those not at risk of serious mental illness. Most recently, researchers found that increased alcohol dependence and family/friend drug use significantly reduced perceptions about an individuals' probation officer, while being older improved an individuals' perceptions (Sloas et al., 2020).

Current Study

The current study complements and expands the existing results found from the MAPIT study data, but does not directly overlap with these prior research questions. The current study builds on the existing research by combining substance users (alcohol and illicit drugs) to determine what patterns of substance use exist while on probation and the impact, if any, the trajectories of substance use have on later re-arrest. This study complements the original aim of MAPIT, but differs by looking beyond the impact of the research study arms to examine substance use patterns and how those patterns impact later outcomes. The current study expands the prior MAPIT studies by examining re-arrest as an outcome. To accomplish these aims, this dissertation addresses the following research questions: *1) What are the patterns of substance use among individuals while on community supervision?; 2) What factors predict group membership in the substance use trajectories?; and, 3) Do the substance use trajectories predict re-arrest and/or time until re-arrest?*

CHAPTER FOUR: METHODOLOGY

This study explores trajectories of substance use among probationers and if these trajectories predict re-arrest and/or time to re-arrest, using data collected in the multi-site, randomized controlled trial, MAPIT. Analysis for this study includes three phases (Figure 6). First, group-based trajectory modeling (GBTM) examines if there are distinct trajectory groups of substance users in the six-months post-baseline. Second, the trajectory profiles are examined using bivariate statistics to identify predictors of the trajectories. Finally, logistic regression and Cox proportional hazards models are used to determine if the trajectory groups predict re-arrest and/or time to re-arrest.

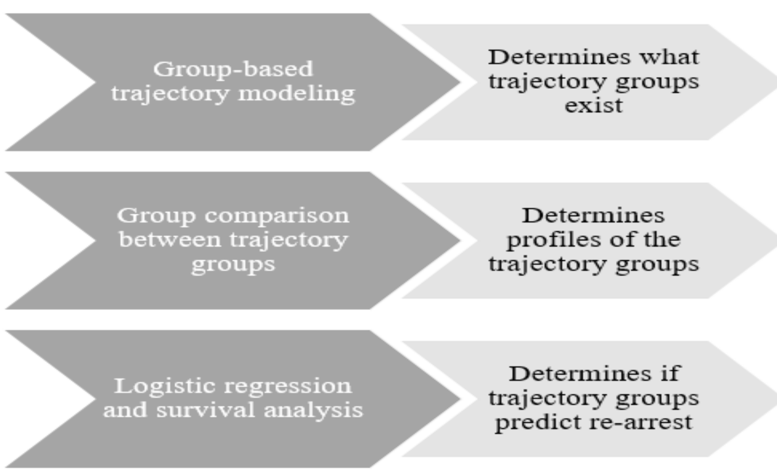


Figure 6: Phases of Analysis

Data Sources

This study uses two data sources: 1) self-report interview data, and 2) administrative arrest data. The self-report interview data comes from in-depth interviews conducted with individuals who consented to participate in the MAPIT study. Trained researchers conducted these interviews at three time points during the study: baseline, two-months post-baseline, and six-months post-baseline. The in-person baseline interview took approximately two hours to complete and covered multiple aspects of the individual's life including drug and alcohol use, demographics, substance abuse treatment history, criminal justice history, physical and mental health history, sexual risk behaviors, traumatic experiences, social support, and psychosocial information. The time-stable predictors in this study (discussed below) come from the baseline interview.

The two-month interview typically took place over the phone and lasted approximately 30 minutes. This interview collected information such as the individual's substance use and treatment, employment changes, living arrangement changes, and criminal justice involvement since the baseline interview. The six-month interview took approximately one and one-half hours to complete in-person. This interview collected similar information as the baseline such as drug and alcohol use, substance abuse treatment, criminal justice involvement, physical and mental health, sexual risk behaviors, social support, and psychosocial information. The interviewer grounded each section of the six-month interview back to the last interview, whether it was the baseline or the two-month interview. Researchers were unable to locate some individuals for the two-month interview, but did find them for the six-month interview. If this happened, the interviewer asked the questions to cover the period since the prior interview. Individuals received gift card incentives for each interview and, as applicable, MAPIT or MI sessions completed.

The administrative arrest data comes from the respective sites state information systems. Both sites provided arrest data from their respective Criminal Justice Information Systems (CJIS). In Maryland, Maryland's Department of Public Safety and Correctional Services maintains CJIS, which contains records for all reportable events (e.g., arrests) in the state. In Texas, the Texas Department of Public Safety ensures collection of these electronic criminal justice records. Data from both states provides information on the dates that arrests occurred and the related charged offense(s) for each arrest. After an initial data request from each site for the MAPIT study participants within their information data system, the researchers made follow-up requests for any missing participants to ensure as complete data collection as possible.

Current Study Sample

Figure 7 depicts the study flow for determining the current study's final sample size. Of the 360 participants randomized into the original MAPIT study, 21 of those individuals were lost to any follow-up and 11 individuals were further lost to the six-month follow-up. Another 16 individuals were removed for missing more than two days of follow-up substance use data, while 15 individuals were removed for missing arrest outcome data. Researchers removed another 22 cases from the original study's analyses because they were missing baseline substance use data that corroborated their substance use reported during the screening process. These individuals had reported at least one day of binge alcohol use (>=five drinks per day for men; >=four drinks per day for women) or one day of any illicit drug use in the 90 days before the interview at screening, but then reported substance use that didn't meet this threshold during the baseline interview. Given the contradictory information provided by the individuals, these cases were deemed invalid, thus they were removed from the analysis.

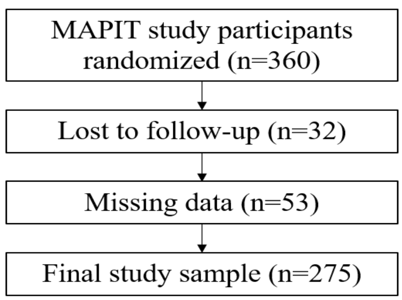


Figure 7: Study Sample Flow

Within the remaining 275 individuals included in this study's sample, 31 individuals were missing one or two days of data. Examining substance use days surrounding these missing days for each case, the level of use was minimal, typically zero. Due to this, the missing data was assumed to be zero, favoring a conservative replacement value for the missing substance use days. See Appendix B for more detail on how missing data and sample size selection was handled.

Measures

Dependent Variables

Number of Substance Use Days. At each interview, the participant completed the Timeline Follow-back (TLFB) that contained self-reported daily information about substance use. The TLFB allowed for a day-to-day measurement of substance use from the baseline interview until the six-month post-baseline interview. The TLFB is a widely used and reliable method of collecting self-report substance use behavior, including both alcohol and illicit drugs (Fals-Stewart et al., 2000; Hjorthøj et al., 2012; Sobell & Sobell, 1992), as well as a methodology used to measure criminal behavior (Horney et al., 1995; Roberts & Horney, 2010). Most studies that examine agreement rates between the TLFB and other measures (e.g., drug and/or alcohol testing) do find a high rate of agreement; however, as the length of recall increases, then the rate of agreement increases (Hjorthøj et al., 2012). To administer the TLFB, the researchers used a calendar and techniques to ground the participants' memories to aid their recall about substance use behaviors day-to-day within a specified time period.

In a particularly rigorous examination of the TLFB method, Fals-Stewart and colleagues (2000) found that the TLFB had high test-retest validity across substances, but that reliability did worsen when substance use was less stable and patterned. Taking this into consideration, the *number of substance use days per month* served as the outcome measure to create the trajectory groups in the current study. This meant improved reliability in this measure given some of the participants' use was less stable and patterned. Capturing substance use as a count per month is a common measurement in prior substance use studies using these methods (Hser et al., 2008; Hser, Huang, et al. 2007). For the purposes of this study, the researcher defines daily substance use as the number of substance-using days in each 30-day increment following completion of the baseline interview until 180 days post-baseline interview; resulting in six data points in the group-based trajectory analysis. Within each data point, the potential range of data is zero to 30. A day of substance use includes any illicit substance or significant alcohol use. Significant alcohol use indicates binge alcohol use (i.e., four or more drinks for females on a single day and five or more drinks for males on a single day) (National Institute on Alcohol Abuse and Alcoholism, n.d.). A day counts as yes for substance use if the participant reports any illicit substance or significant alcohol on that day. The summation of yes responses within a 30-day time period results in a value of zero to 30. While the six-month follow-up period is a short amount of time, Horney and colleagues (1995) argued that these short follow-ups are valid and important to understanding association between life events and behaviors, particularly when looking at individuals with unstable lives.

Re-arrest. Re-arrest is calculated both as a dichotomous variable and as time until the arrest event (i.e., number of days until event). These outcomes are calculated from the administrative arrest records regarding whether or not an arrest occurred within six to 18 months following the baseline interview. This time frame meant that the re-arrest outcome falls immediately after the six months capturing the trajectory group substance use data. The dichotomous measure indicates yes or no if the event occurred and the time until measures how many days until an arrest occurred in the time period six to 18 months following the baseline interview.

Independent Variables

This research includes both time-stable predictor variables and time-varying covariates. The predictor variables consist of four categories of variables: demographics, prior substance treatment and use history, criminal justice characteristics, and psychosocial. The time-varying covariates include housing in a non-controlled environment, formal substance use treatment attendance, probation officer contacts, and arrests. The predictor variables come from the baseline interview and the time-varying variables come from the follow-up interviews.

Time-stable Predictors.

Demographic variables. The demographic characteristics includes gender, age, race, housing stability, education, employment, and relationship status, and were self-reported by the participants during the baseline assessment. Gender, race, housing stability, education, employment, and relationship status are dichotomously measured variables (0, 1). Gender captures male or female, as the participant self-identifies. Race captures whether the participant is either white or non-white. Housing stability measures whether the participant had stable housing within the 90 days before the baseline interview. This measure is coded as non-stable if the participant indicated either being homeless, living outside, in a shelter, transitional housing, or single room occupancy hotel in the 90 days prior to the baseline interview. Education indicates if the participant had a high school diploma or not (not including a GED). Employment measures if the participant was unemployed in any capacity (i.e., not full-time, part-time, student, retired/disability) in the 90 days before the baseline interview. Relationship status measures whether the participant was married or in a committed relationship at the time of the baseline interview. The participants' age at the baseline interview is a continuous variable.

Prior substance treatment and use history variables. The prior substance treatment and use history variables include lifetime prior treatment, age of first use, recent hard drug use, intravenous (IV) drug use, consequences experienced from substance use, family/peer drug use, and Addiction Severity Index-Lite (ASI-Lite) drug and alcohol severity scores. Lifetime prior treatment, age of first illegal drug use or alcohol use, recent hard drug use, IV drug use, and problem drug use are measured as dichotomous variables (0/1). Lifetime prior treatment measures if the participant had ever attended any substance use treatment, not including self-help groups like Narcotics Anonymous, Cocaine Anonymous, or Alcohol Anonymous.[2] Age of first use captures if the participant initiated illegal drug or alcohol use younger than 16 or 16 and up. Recent hard drug use measures if the participant reported any use of opiates, cocaine, hallucinogens, inhalants, amphetamines, barbiturates, or illicit prescription drugs in the 90 days before the baseline interview as captured on the baseline TLFB. IV drug use measures if the participant reported injecting any drugs not prescribed by a doctor in the six months before the baseline interview.

Consequences experienced from substance use, family and peer drug use, ASI alcohol score, and ASI drug score are continuous variables. Consequences experienced from substance use come from an 18-item scale that captures six subscales (i.e., health, relationships, personal, risky behavior, responsibilities, and legal) (see Figure 8). These

[2] Self-help groups tend to vary widely in their format (e.g., level of clinical skill by leaders, manualization) which can influence the potential benefit of these approaches (Kelly et al., 2020). Therefore, this measure is narrowed to more structured, formalized treatment experiences in the individuals' past that would be expected to have a more consistent impact on the individuals' substance use behavior. Further, including a broader definition of prior treatment experience to include self-help groups would not have substantively changed the results (additional analysis not included here).

items are modified from the drug and alcohol inventories of consequences (Tonigan & Miller, 2002; Miller et al., 1995). This scale is scored by summing the responses,

- My physical health or appearance was harmed.
- My relationship with friends or family members was damaged.
- I was anxious or depressed.
- I had an accident while I was under the influence.
- I had money problems.
- Social or legal authorities were involved in my life (Child Protective Services, Probation/Parole, Court).

Figure 8: Sample Consequences of Use Questions

with a higher score indicating greater consequences experienced in the three months prior to the baseline interview. Family and peer drug use indicates if the participant reported using substances with their family or friends in the six-months before the baseline interview. This measure consists of family (three items) and friends (one item) questions averaged based on asking how often the individual used drugs with spouses, parental figures, siblings, or peers in the six-months before the baseline interview. The ASI-lite alcohol severity score consists of six questions (alpha= 0.76) and the drug severity score consists of 13 questions (alpha= 0.77) (McLellan et al., 1999). The algorithm for the composite scores comes from the ASI-Lite scoring guide (McGahan et al., 1986).

Criminal justice variables. The criminal justice variables include criminal justice static risk score, length of probation sentence, time on probation at the baseline interview, drug testing condition, drug treatment condition, and instant offense for this probation. Criminal justice static risk score is additive from seven questions with a possible score ranging zero to nine. These include questions such as 'How many times have you been arrested before this current offense?' and 'Were you arrested before you turned 16?'. The length of the individuals' probation sentence is a continuous measure of the number of sentenced months. The time on probation at the baseline interview measures the number of days the individual had already been on probation at the baseline interview. Some of the individuals had not actually started probation at the time of the baseline interview and these cases were coded as zero days on probation so far. During analysis of the original MAPIT study data, some individuals violated the eligibility criteria for the maximum of 30 days or less on probation at start. While these cases were removed from the MAPIT study findings (Lerch et al., 2017), these cases are included in the current studies' analyses to predict the trajectory groups. Drug testing condition and drug treatment condition are dichotomous measures (0/1). Drug testing condition indicates if the participants had a requirement on his/her probation to be drug tested as of the baseline interview. Drug treatment condition indicates if the participant had been required by probation to attend substance abuse treatment as of the baseline interview. The instant offense for this probation measures whether or not the individuals' current probation offense was a drug offense or not.

Psychosocial variables. The psychosocial variables consist of self-esteem, decision-making, hostility, risk taking, recognition, mental health, social support, and self-determination. The self-esteem (six items; alpha=0.83), decision-making (nine items; alpha=0.71), hostility (eight items; alpha=0.76), and risk taking (seven items; alpha=0.69) measures are subscales from the validated CJ Client Evaluation of Self and Treatment

Intake (CJ-CEST) (Institute of Behavioral Research, Texas Christian University, 2005). Each of these subscales measure the emotional, social, and motivational functioning of the participant at the baseline assessment. All of the subscales are scored on a one to five scale and by taking the mean response on each subscale. The recognition scale (eight items; alpha=0.93) is calculated by combining the CJ-CEST subscales of problem recognition and desire for help. This scale reflects that the individual had recognition that substance use was causing problems within their life. See Appendix C for more details on the creation of this recognition variable.

The mental health measures comes from the Co-Occurring Disorders Screening Instrument for Mental Disorders (CODSI-MD) and Severe Mental Disorders (CODSI-SMD) (Sacks et al., 2007). Each subscale, mental disorders (seven items) and severe mental disorders (four items), are summative scores. Following the scoring guide, the researcher dichotomized each of these scores to indicate the potential risk of either a mental health disorder or severe mental health disorder. A score of three or higher on the mental health measure indicates a potential mental health disorder, and a score of two or higher on the severe mental health measure indicates a potential severe mental health disorder.

Social support represents the extent to which the participant felt they had people in their lives that support them and is captured using the Social Support Instrument (Sherbourne & Stewart, 1991). The social support scale consists of 18 items which are calculated by taking the mean response, with a higher score indicating greater social support (alpha= 0.94). Self-determination is the extent to which the participant recognizes their own feelings and self, and felt they had choice in their life (Sheldon & Deci, 1993). This is a 10-item scale calculated by taking the average of the responses, with the higher the score indicating more self-determination (alpha= 0.73).

Additional control variables. Two additional control variables are study arm and study site. The study arms consist of: 1) supervision as usual (SAU); 2) motivational computer program (MAPIT); and, 3) in-person motivational interviewing (MI). For analyses, the study arms MAPIT and MI are dummy coded (0/1), with the identified study arm assigned a one. Given the primary study findings on substance use (Lerch et al., 2017), it is unlikely the study arm will impact the dependent variables in the current study; however, due to the minimal chance study arm may impact the outcomes this is examined as a predictor.

Additionally, the original MAPIT study involved two study sites that are structured differently. Baltimore, MD processes individuals by assessing them for substance use problems after the court has placed a condition on them for substance treatment. Individuals may be sent back for assessment if their probation agent recognizes they are struggling with substances (e.g., failing a drug test). Dallas, TX has a specialized assessment unit that provides recommendations to the court before the sentencing phase after an extensive assessment process. In most cases, the assessment units' recommendations are followed by the court. Given the differences between sites and that these differences could impact the current study's outcomes, study site is examined as a predictor.

Time-varying Predictors. The housing in a non-controlled environment and formal treatment attendance variables are calculated from the TLFB collected during the six months after the baseline interview. The housing in a non-controlled environment captures how many days in a month the participant spent the night in the community. The community is defined as staying at home, with family or friends, in paid lodging, in an abandoned structure, outside, at a shelter or transitional house, or a halfway-house. These living arrangements represent living situations that are not controlled and in which the participant should have greater access to use substances. The formal treatment attendance measures how many days in a month the participant reported attending group sessions, inpatient treatment (30 days or less), intensive outpatient, medication treatment, or residential treatment (>30 days). Involvement in these types of formalized treatment may impact the trajectories of substance use participants reported. These calculations result in six 30-day time periods for each variable.

Probation contacts captures how many times per month the participant saw their probation officer. This is measured by questions about frequency of meeting with their probation officer on the two-month follow-up and six-month follow-up interviews. This could be any contact the participant had with their probation officer. For the analysis, time points one and two reflect the average number of times reported on the two-month follow-up and time points three, four, five, and six reflect the number of times reported on the six-month follow-up. If a participant missed the two-month follow-up interview, then time points one and two reflect the average number of times reported on the six-month follow-up. The number of arrests per month in the six months following the baseline interview are calculated using the administrative arrest data. These calculations result in six time points, one for each month following the baseline interview.

Analysis

Analysis for this study included descriptive statistics, group-based trajectory modeling (GBTM), determination of trajectory profiles using bivariate statistics, logistic regression, and Cox proportional hazards model.

Phase One: Group-based Trajectory Models

GBTM is an approach that aims to classify individuals into groups based on their patterns of an outcome variable (i.e., substance use in the current study) (Nagin, 1999; Nagin & Odgers, 2010). This semi-parametric approach allows for multinomial patterns (i.e., trajectory directions varying between individuals) and groups individuals according to similar patterns of change over time (Andruff et al., 2009; Nagin & Odgers, 2010). GBTM does not allow for variance within groups, only between groups (Andruff et al., 2009; Berlin et al., 2013; Bushway et al., 2009; Jung & Wickrama, 2008; Kreuter & Muthen, 2008; Nagin & Odgers, 2010). GBTM is the method chosen due to this study's small sample size (Berlin et al., 2013) and the assumption that the substance use patterns do not represent distinct subpopulations, but rather groups that are more similar to one another (Frankfurt et al., 2016; Morris & Slocum, 2012; Nagin & Odgers, 2010). In other words, the groups identified by the GBTM are not different enough from one another to truly call them subpopulations; rather, they are part of underlying distribution patterns falling along a continuum of substance use.

The researcher chose to use the PROC TRAJ macro in SAS to run the GBTM (Andruff et al., 2009; Jones & Nagin, 2007). A zero-inflated Poisson model is used because of the skew toward zero present in the outcome of substance use days (Britt et al., 2017; Morris & Slocum, 2012; Nagin & Land, 1993; Roeder et al., 1999). The Bayesian Information Criterion (BIC) is used to determine the best model fit. The BIC expresses the best fit model by being the least negative value as compared to other models. This value should ideally be at least 10 less than the previous model to demonstrate strong evidence for model selection (Frankfurt et al., 2016; Jung & Wickrama, 2008; Morris & Slocum, 2012; Nagin, 1999; Nagin & Odgers, 2010). For model adequacy, the posterior probabilities are examined. Posterior probabilities are used post hoc to determine the probability that an individual case belongs in a trajectory group. These posterior probabilities are averaged to determine the internal reliability of membership assignment within each trajectory group (Andruff et al., 2009). A minimum of 0.70 average posterior probability is necessary to indicate appropriate group membership (Andruff et al., 2009; Frankfurt et al., 2016; Jung & Wickrama, 2008; Morris & Slocum, 2012; Nagin, 1999; Nagin & Odgers, 2010). The odds of correct classification (OCC) are then calculated and examined to meet the criteria of exceeding five (Nagin & Odgers, 2010).

Initial models are used to determine the appropriate number of groups using quadratic trends for all trajectories. The quadratic trend allows for increasing, decreasing, and stable changes (Andruff et al., 2009). Once the number of groups are determined using the model fit and adequacy criteria, the polynomial orders are reduced until the polynomial is significant for each group (Andruff et al., 2009). The final model is examined to determine that the percentage of the sample within each group is at least five percent (Andruff et al., 2009; Nagin & Odgers, 2010).

Phase Two: Predictors of Substance Use Group Membership

The researcher examined the profiles of the trajectory groups using ANOVAs and chi-square significance tests for the time-stable predictor variables. Conducting these bivariate statistics allows examining the relationship between the time-stable predictor variables and the groups without confounding the relationship with other predictor variables. Additionally, these bivariate statistics allow for reducing the number of time-stable predictor variables put into the final model. This approach creates a model that is as parsimonious as possible, reducing the chance for spurious findings that could occur by introducing so many predictor variables (i.e., 33 time-stable and four time-stable predictors) with the current study's sample size. This is a common practice with other statistical methods, such as logistic regression, with a general rule being to have at least 10 cases per one predictor variable (Vittinghoff & McCulloch, 2006). Additionally, keeping the model parsimonious follows general best practice with GBTM, especially with a lower sample size that limits power (Andruff et al., 2009). Then, the time-stable predictor variables found to be significantly related to the trajectory groups in the bivariate statistics are placed simultaneously into the PROC TRAJ code to allow the covariates to predict group membership and showing the cumulative risk (Nagin & Odgers, 2010). Next, the time-varying predictor variables are placed into the PROC TRAJ code alone to examine these variables impact on the groups. For the final GBTM, the time-stable (i.e., those significant from the bivariate statistics) and time-varying predictor variables are combined into the PROC TRAJ code.

Phase Three: Predictors of Re-arrest

The group classification variable from the final trajectory group model is imported into SPSS for the following analyses. ANOVA and chi-square tests are run between the time-stable independent variables and the dichotomous re-arrest outcome variable. Logistic regression is used to predict re-arrest within six to eighteen months post baseline completion. This timing allows for assessing re-arrest for the one year after the six-month timeframe considered by the trajectory model. Initially, a model containing only the substance use trajectory groups variable is used to predict re-arrest. Then, the time-stable independent variables not incorporated into the substance use trajectory groups are entered into a logistic regression with the categorical substance use trajectory groups variable. Finally, all of the time-stable independent variables and the categorical substance use trajectory groups are placed into a logistic regression predicting re-arrest.

Next, a Cox proportional hazards model is used to examine the time until arrest for the six to 18 month period post baseline assessment. This model will be used to identify which variables impact the likelihood of experiencing re-arrest. This method is widely accepted in criminology as a superior way to examine recidivism because it takes into account all the information available regarding time of the event beyond only a dichotomous accounting of the event (Allison, 2014; Mills, 2015). A Cox proportional hazards model, a semi-parametric approach, allows for multiple covariates and makes "no assumption about the shape of the hazard" (Mills, 2015, p. 16-17). The arrest data is right censored because there are some individuals who did not experience a re-arrest by the last observation (Mills, 2015).

CHAPTER FIVE: RESULTS

Descriptive Statistics

Tables 1 through 4 portray the study's descriptive statistics. Table 1 contains the time-stable independent variables that are categorical, while Table 2 contains the continuous time-stable independent variables. Participants are primarily male, non-white, unemployed, and an average age of 35 years old. Most of the participants do not have a high school diploma and are in a committed relationship. Approximately half of the participants have previously been in substance use treatment and used a hard drug at least once in the 90 days before the baseline interview. The majority of the sample initiated substance use at 15 years old or younger.

Few participants recently used intravenous drugs. Participants report low for consequences of substance use, family/peer drug use, ASI alcohol severity, and ASI drug severity. Nearly 75% of the participants have a court ordered drug testing condition, while only 36% have a court ordered condition to attend substance use treatment. Forty-four percent of the participants are on probation for a drug-related offense. The study sample are on average a moderate risk level and serving an average of 33 months on probation. The participants have been on probation for about 44 days before the baseline interview. About 12% of the sample are at risk of a mental health disorder, while 38% are at risk for a severe mental health disorder. The participants score moderately high for self-esteem, decision-making, social support, and self-determination, while they score moderately on hostility, risk taking, and recognition. About 61% of the sample is from Dallas and equally distributed across the original randomized study arms.

Table 1: Time-Stable Variables Frequencies and Percentages (n=275)

Variables	Frequency Positive	Percent Positive	Missing
Demographics			
Female	85	30.9%	0
Nonwhite	214	78.1%	1
Stable housing	214	77.8%	0
High school diploma	105	38.2%	0
Committed relationship	154	56.0%	0
Unemployed	147	53.5%	0
Prior Substance Treatment and Use History			
Lifetime prior treatment	136	49.5%	0
Initiated use 15 and under	178	64.7%	0
Hard drug use	143	52.0%	0
Recent IV drug user	24	8.7%	0
Criminal Justice			
Drug testing condition	200	72.7%	0
Drug treatment condition	99	36.0%	0
Drug instant offense	121	44.0%	0
Psychosocial			
Risk of mental disorders	32	11.7%	1
Risk of severe mental disorders	103	37.6%	1
Additional controls			
MI	88	32.0%	0
MAPIT	94	34.2%	0
SAU	93	33.8%	0
Dallas	167	60.7%	0

Table 3 portrays the descriptive statistics for the time-varying independent variables. While the number of days housed in a non-controlled environment remain high overall, the average number of days declines across the months. The average number of days attending formal treatment continuously rises across the six months of follow-up, but remains relatively low. The probation contacts and number of arrests are relatively stable across the follow-up months.

Table 2: Time-Stable Variables Mean, Standard Deviation, Min., Max. (n=275)

Variables	Mean	SD	Minimum	Maximum	Missing
Demographics					
Age	34.7	11.5	18.0	63.0	0
Prior Substance Treatment and Use History					
Consequences of use	15.5	12.4	0.0	50.0	1
Family/peer drug use	1.8	0.7	1.0	4.8	0
ASI alcohol severity	0.2	0.2	0.1	1.0	0
ASI drug severity	0.1	0.1	0.0	0.6	0
Criminal Justice					
Criminal justice static risk score	4.3	2.0	0.0	8.0	0
Months sentenced to probation	32.8	67.4	4.0	1095.00	0
Days on probation*	43.9	166.7	0.0	2124.00	1
Psychosocial					
Self-esteem	35.3	7.9	11.7	50.0	1
Decision-making	37.0	4.9	21.1	50.0	2
Hostility	26.7	6.9	10.0	46.3	2
Risk taking	28.4	6.2	14.3	45.7	1
Recognition	27.8	9.3	10.0	50.0	1
Social support	3.8	1.1	1.0	5.0	0
Self-determination	3.8	0.9	1.4	5.0	4

* Given the large range for this variable, the potential impact of outliers was examined in sensitive analysis found in Appendix D.

Table 4 shows the descriptive statistics for the number of substance use days by month. Except for a decline in month two use, the remaining months show similar rates of use. Sixty-three participants (22.9%) were arrested in the 6 to 18 months after the baseline interview. Among these individuals, most were arrested one time (73%) with a range of one to three arrests happening during this time. The time until arrest in this time range from 3 to 364 days, with the average number of days being 147 days.

Table 3: Time-Varying Variables Mean, Standard Deviation, Min., Max. (n=275)

	Mean	SD	Minimum	Maximum
Housing in a non-controlled environment				
Month 1	28.9	4.4	1	30
Month 2	28.4	6.3	0	30
Month 3	27.8	7.0	0	30
Month 4	27.1	8.2	0	30
Month 5	26.5	9.1	0	30
Month 6	26.4	9.3	0	30
Formal Treatment Attendance				
Month 1	2.7	7.9	0	30
Month 2	3.2	8.2	0	30
Month 3	3.1	7.5	0	30
Month 4	3.8	8.6	0	30
Month 5	4.2	9.4	0	30
Month 6	4.2	9.5	0	30
Probation officer contacts				
Month 1	2.0	2.4	0	20
Month 2	2.0	2.4	0	20
Month 3	1.8	1.9	0	12
Month 4	1.8	1.9	0	12
Month 5	1.8	1.9	0	12
Month 6	1.8	1.9	0	12
Arrests				
Month 1	0.0	0.2	0	1
Month 2	0.0	0.2	0	1
Month 3	0.0	0.2	0	1
Month 4	0.0	0.2	0	1
Month 5	0.0	0.2	0	1
Month 6	0.0	0.1	0	1

Table 4: Number of Substance Use Days by Month (n=275)

	Mean	SD	Minimum	Maximum
Month 1	6.2	10.4	0	30
Month 2	5.5	9.9	0	30
Month 3	6.6	10.5	0	30
Month 4	6.7	10.6	0	30
Month 5	6.5	11.0	0	30
Month 6	6.6	10.9	0	30

Phase One: Group-based Trajectory Models

The model selection is determined using the BIC, trajectory patterns, and estimated group proportions for seven trajectory models (i.e., two-, three-, four-, five-, six-, seven-, and eight-group models) (Table 5), while the adequacy of the model is determined by examining the average posterior probabilities and odds of correction classification (OCC). Initial analysis included all quadratic models, with the polynomial

Table 5: GBTM Model Selection using BIC and Estimated Group Proportions (n=275)

# of Groups	BIC (N=1650)[1]	BIC (N=275)[2]	Estimated Group Proportions 1	2	3	4	5	6	7	8
2	-4411.52	-4402.56	59.3	40.7						
3	-3938.08	-3925.54	48.8	26.0	25.1					
4	-3740.90	-3724.77	46.3	19.6	12.3	21.8				
5	-3647.31	-3627.60	45.9	13.2	12.8	7.8	20.3			
6	-3490.98	-3467.68	45.8	12.8	11.5	8.7	7.7	13.5		
7	-3481.91	-3455.03	22.2	24.3	12.3	11.4	8.7	7.6	13.5	
8	-3491.51	-3461.05	32.9	13.9	8.0	10.9	8.7	10.6	14.9	0.0
6	**-3478.14**	**-3458.43**	**45.7**	**12.8**	**11.5**	**8.8**	**7.7**	**13.5**		

BIC[1]=overall sample size; BIC[2]=subject sample size

order adjusted in the final model. The BIC is lowest for the seven-group model and the estimated group proportions were all above 5.0%. However, examining the seven- group trajectories (Figure 10) reveals that this model offers no interpretable improvement over the six-group model (Figure 9). In the seven-group model, trajectories one and two are indiscernible from one another, thus resulting in the selection of the six-group model as the better model. Next, the polynomial order of the trajectories are adjusted to the highest level (i.e., intercept, linear, quadratic) within each group to determine the order that the parameter estimates reach significance (Table 6). The quadratic model is determined to fit the data best (Figure 11).[3]

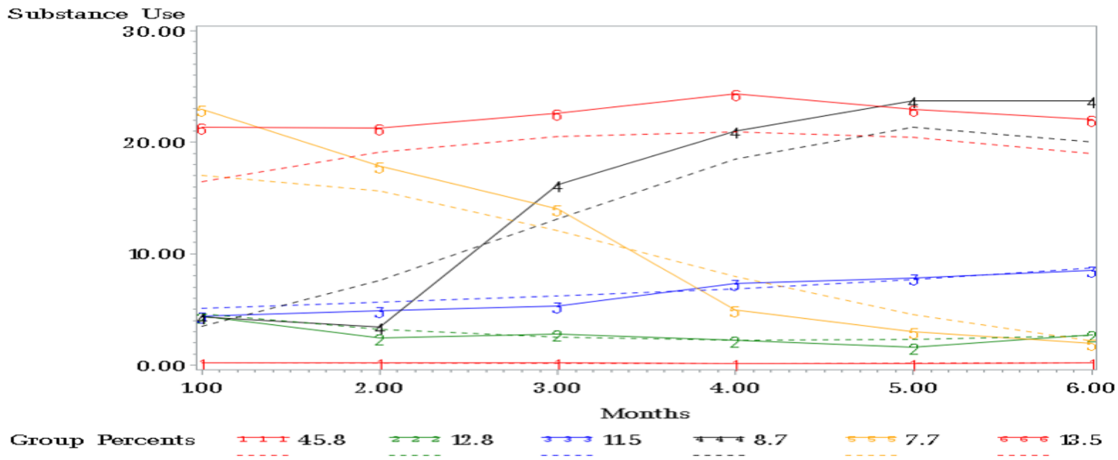


Figure 9: 6-Group Substance Use Trajectories (222222, Iorder 2)

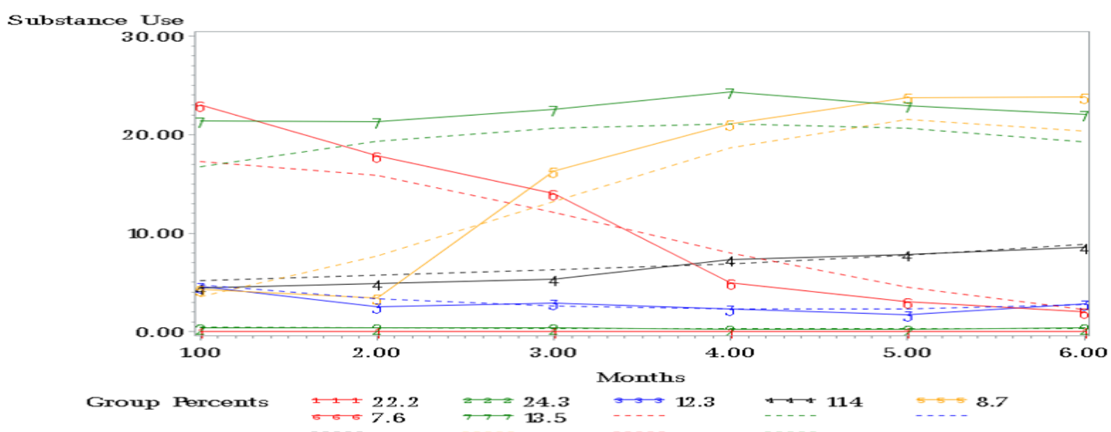


Figure 10: 7-Group Substance Use Trajectories (2222222, Iorder 2)

[3] Further sensitivity analysis testing of five- and seven-group models presented in Appendix D.

Table 6: GBTM with 6-Group Substance Use Trajectories (n=275)

Group	Parameter Estimate	t-statistic	P-value
Abstainers			
Intercept	-1.44	-13.79	<0.001
Low-moderate			
Intercept	2.66	14.99	<0.001
Linear	-0.75	-5.87	<0.001
Quadratic	0.09	4.70	<0.001
Moderate-increasing			
Intercept	2.21	11.14	<0.001
Linear	-0.12	-1.03	0.3011
Quadratic	0.03	1.96	0.0506
Increasing			
Intercept	0.92	3.24	0.0012
Linear	0.89	6.65	<0.001
Quadratic	-0.08	-5.28	<0.001
Decreasing			
Intercept	3.43	28.07	<0.001
Linear	-0.06	-0.56	0.5731
Quadratic	-0.05	-3.11	0.0019
High			
Intercept	3.30	190.66	<0.001

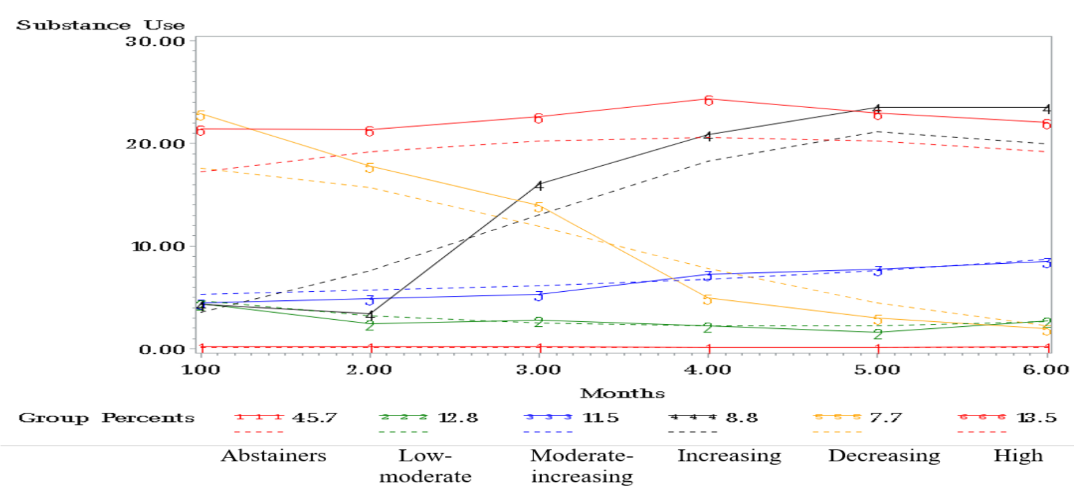


Figure 11: 6-Group Substance Use Trajectories (022220, Iorder 2)

One group displayed no substance use and are referred to as "abstainers." Another group maintains moderate substance use with a slight increase across time (i.e., "moderate-increasing" users). A group of "low-moderate" users starts at the same level as the moderate-increasing users, but decreases slightly across time. A group of "increasing" users start at the same level as the low-moderate and moderate-increasing groups, but increase to the highest use levels. Substance use within the group of "high" users remains high during the entire time. Lastly, a group of "decreasing" users started at the same level as the high users group, but drastically decreased across time. Examining the average posterior probabilities (minimum 0.7) and OCC (minimum 5) reveals that both exceeded the minimum values indicating that the six-group model adequately assigns individuals to the trajectory groups (Table 7).

Table 7: GBTM Diagnostics (n=275)

Group	Proportion in Group	Average Posterior Probability	Odds of Correct Classification
Abstainers	0.46	0.986	81.30
Low-moderate	0.13	0.941	109.01
Moderate-increasing	0.12	0.921	90.00
Increasing	0.09	0.940	161.76
Decreasing	0.08	0.947	216.23
High	0.13	0.924	77.924

<u>Phase Two: Predictors of Substance Use Group Membership</u>

Bivariate Statistics with Time-Stable Covariates

Table 8 shows the bivariate statistics of all the time-stable covariates across the six-group model. Among the demographics, high school diploma (X^2(5, N = 275) =

10.67, p = .06) is significantly related to the group assignment. Individuals with a high school diploma are less likely to be within the high user and increasing user groups. Several of the prior substance treatment and use history time-stable variables are significantly associated with group assignment. Individuals having prior treatment ever are more likely to be within the low-moderate, decreasing, and high user groups (X^2(5, N = 275) = 11.18, p = .05), whereas individuals who began using substances at 15 years old or younger are less likely to be in the abstainer or moderate-increasing user groups (X^2(5, N = 275) = 13.17, p = .02). The decreasing users report experiencing more consequences for their substance use (F(5, 268)=4.74, p<.001). Abstainers reported less family/peer drug use, whereas the increasing, decreasing, and high user groups report more family/peer drug use (F(5, 269)=4.32, p=.001). The moderate-increasing and abstainer groups report lower ASI drug severity scores (F(5, 269)=4.71, p<.001).

Among the criminal justice variables, only drug testing condition is significantly related to group assignment, with the increasing and high user groups being less likely to have a drug testing condition (X^2(5, N = 275) = 16.20, p = .01). Self-esteem, hostility, risk taking, recognition, and self-determination are significantly related to group assignment. Decreasing users report less self-esteem (F(5, 268)=2.26, p=.05) and increased hostility (F(5, 267)=3.32, p=.01). Abstainers are less likely to report taking risks (F(5, 268)=4.91, p<.001) and recognition of needing help with their substance use (F(5, 268)=4.14, p=.001). Decreasing users report increased recognition of needing help. Decreasing and high user groups report less self-determination (F(5, 265)=2.29, p=.05).

Table 8: Bivariate Statistics of the Time-Stable Predictors by Substance Use Trajectories

Predictor	Substance Use Trajectory Groups						P-value
	Abstainers N(%)/M±SD	Low-moderate N(%)/M±SD	Moderate-increasing N(%)/M±SD	Increasing N(%)/M±SD	Decreasing N(%)/M±SD	High N(%)/M±SD	
Demographics							
Female	34 (26.8)	10 (29.4)	10 (31.3)	9 (39.1)	7 (35.0)	15 (38.5)	0.703
Nonwhite	102 (80.3)	22 (64.7)	22 (71.0)	20 (87.0)	17 (85.0)	31 (79.5)	0.260
Stable housing	**109 (85.8)**	**34 (70.6)**	**25 (78.1)**	**16 (69.6)**	**11 (55.0)**	**29 (74.4)**	**0.024**
High school diploma	50 (39.4)	16 (47.1)	17 (53.1)	5 (21.7)	8 (40.0)	9 (23.1)	0.058
Committed rel.	71 (55.9)	20 (58.8)	18 (56.3)	16 (69.6)	7 (35.0)	22 (56.4)	0.368
Unemployed	65 (51.2)	16 (47.1)	13 (40.6)	17 (73.9)	13 (65.0)	23 (59.0)	0.138
Age	35.7 ± 11.7	34.5 ± 11.8	33.8 ± 10.6	31.8 ± 12.2	33.1 ± 11.1	35.3 ± 11.6	0.692
Prior substance treatment and use history							
Lifetime prior treatment	**54 (42.5)**	**21 (61.8)**	**14 (43.8)**	**9 (39.1)**	**13 (65.0)**	**25 (64.1)**	**0.048**
Initiated 15 and under	**72 (56.7)**	**23 (67.6)**	**18 (56.3)**	**20 (87.0)**	**15 (75.0)**	**30 (76.9)**	**0.022**
Hard drug use	53 (41.7)	21 (61.8)	18 (56.3)	15 (65.2)	13 (65.0)	23 (59.0)	0.059
Recent IV drug user	7 (5.5)	3 (8.8)	4 (12.5)	3 (13.0)	2 (10.0)	5 (12.8)	0.605
Consequences of use	**12.4 ± 10.7**	**18.7 ± 13.7**	**16.3 ± 12.0**	**15.0 ± 11.5**	**24.3 ± 14.7**	**18.2 ± 12.9**	**<0.001**
Family/peer drug use	**1.6 ± 0.7**	**1.8 ± 0.7**	**1.8 ± 0.7**	**2.1 ± 0.9**	**2.2 ± 1.0**	**2.0 ± 0.7**	**0.001**
ASI alcohol severity	0.2 ± 0.1	0.2 ± 0.2	0.3 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.2	0.588
ASI drug severity	**0.1 ± 0.1**	**0.2 ± 0.2**	**0.1 ± 0.1**	**0.2 ± 0.1**	**0.2 ± 0.2**	**0.2 ± 0.1**	**<0.001**
Criminal justice							
Drug testing condition	**102 (80.3)**	**24 (70.6)**	**23 (71.9)**	**11 (47.8)**	**17 (85.0)**	**23 (59.0)**	**0.006**
Drug treatment cond.	43 (33.9)	14 (41.2)	11 (34.4)	8 (34.8)	11 (55.0)	12 (30.8)	0.508
Drug instant offense	53 (41.7)	18 (52.9)	16 (50.0)	8 (34.8)	7 (35.0)	19 (48.7)	0.603
Risk score	4.1 ± 2.2	4.2 ± 2.0	4.1 ± 2.0	4.3 ± 1.8	5.1 ± 1.8	4.6 ± 1.9	0.396
Probation sentence	41.1 ± 97.0	28.4 ± 23.2	24.9 ± 16.4	20.8 ± 9.7	23.6 ± 13.0	27.8 ± 16.8	0.579
Days on probation	53.2 ± 226.8	30.1 ± 70.1	31.9 ± 65.4	48.6 ± 121.4	37.5 ± 80.0	36.2 ± 101.4	0.969
Psychosocial							
Risk mental disorders	9 (7.1)	4 (11.8)	5 (15.6)	3 (13.0)	6 (30.0)	5 (12.8)	0.088
Risk severe mental disorder.	41 (32.5)	11 (32.4)	14 (43.8)	8 (34.8)	11 (55.0)	18 (46.2)	0.290
Self-esteem	**36.4 ± 7.1**	**34.6 ± 6.9**	**34.9 ± 7.8**	**36.6 ± 9.3**	**30.4 ± 10.3**	**34.7 ± 8.4**	**0.049**
Decision-making	37.5 ± 4.6	36.8 ± 4.5	36.6 ± 4.2	36.0 ±5.3	36.6 ± 4.8	36.6 ± 6.3	0.724
Hostility	**25.4 ± 6.1**	**27.1 ± 7.3**	**26.3 ± 7.4**	**28.9 ± 6.6**	**31.1 ± 6.4**	**27.6 ± 7.6**	**0.006**
Risk taking	**26.6 ± 5.3**	**30.2 ± 7.9**	**29.6 ± 6.5**	**31.0 ± 4.9**	**31.0 ± 6.6**	**29.1 ± 6.3**	**<0.001**
Recognition	**25.0 ± 8.7**	**29.5 ± 9.1**	**27.6 ± 8.8**	**26.1 ± 9.2**	**34.1 ± 9.1**	**30.4 ± 10.0**	**0.001**
Social support	4.0 ± 1.0	3.7 ± 1.0	3.7 ± 1.2	4.1 ± 1.2	3.4 ± 1.2	3.7 ± 1.0	0.169
Self-determination	**3.9 ± 0.8**	**3.7 ± 0.7**	**3.8 ± 0.9**	**3.9 ± 0.8**	**3.4 ± 0.9**	**3.5 ± 1.0**	**0.046**
Additional controls							
MI	42 (33.1)	10 (29.4)	10 (31.3)	4 (17.4)	5 (25.0)	17 (43.6)	0.381
MAPIT	38 (29.9)	13 (38.2)	12 (37.5)	12 (52.2)	9 (45.0)	10 (25.6)	0.217
Dallas	**91 (71.7)**	**21 (61.8)**	**19 (59.4)**	**8 (34.8)**	**9 (45.0)**	**19 (48.7)**	**0.004**

Abstainers are more likely to be in Dallas while increasing users are less likely to be in Dallas ($X^2(5, N = 275) = 17.32$, $p = .004$).

Six-Group Trajectories Incorporating Time-Stable Covariates

The time-stable variables significantly related to the substance use trajectories are placed into trajectory models to determine how these characteristics predict the probability of group membership cumulatively. Figure 12 visually demonstrates that including the time-stable covariates did not significantly change the substance use trajectories. The average posterior probabilities and OCC indicate that the model adequately assigns individuals to groups (Table 9). The coefficients revealed that among

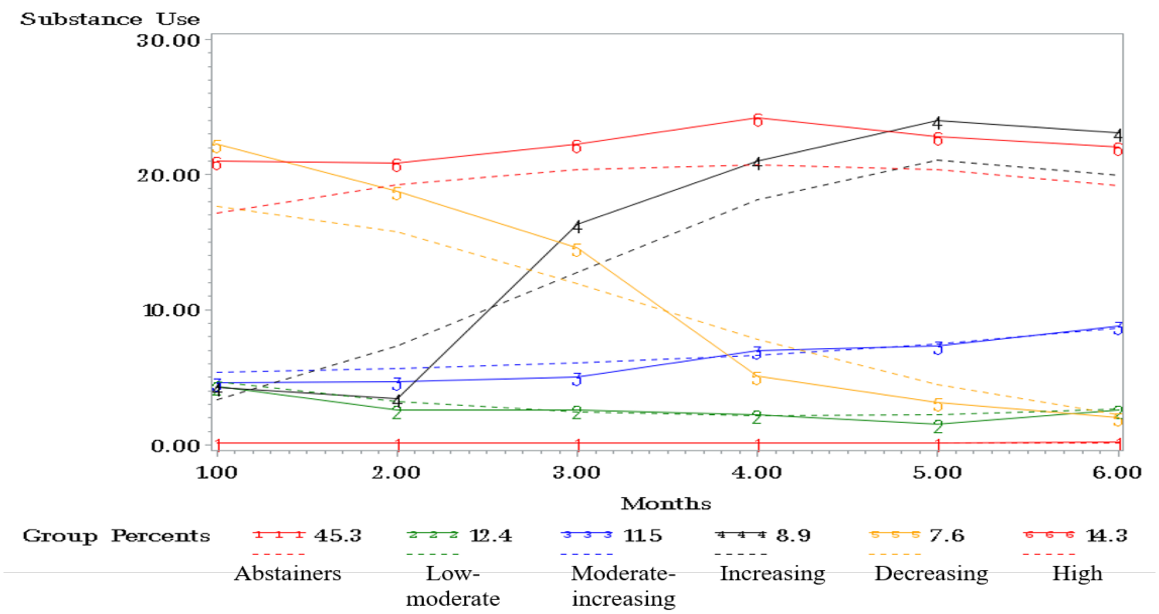


Figure 12: 6-Group Substance Use Trajectories with Time-Stable Covariates

the covariates there were some risk factors (i.e., positive coefficients meaning that the characteristic puts the individual at higher risk for a higher trajectory of substance use) and protective factors (i.e., negative coefficients meaning that the characteristic puts the individual at lower risk for a higher trajectory of substance use) for group membership. The abstainer group serves as the reference group in these results. For the low-moderate, (est=0.08; p= 0.05), moderate-increasing (est= 0.09; p= 0.02), and increasing (est=0.17;

p=0.004) user groups, reporting higher risk taking significantly puts them at risk of being in these respective groups as compared to the abstainer group. Family and peer drug use is a risk factor for being in the increasing (est=0.78; *p*=0.04) and decreasing (est=0.90; *p*=0.03) user groups. For the increasing user group, initiating substance use under the age of 16 is a risk factor (est= 1.68; *p*= 0.04). Individuals in Baltimore are at higher risk to be in the increasing user group (est=-1.83; *p*=0.02). Having stable housing is a protective factor for the decreasing user group (est=-1.26; *p*=0.05), while having a drug testing condition was a protective factor in the high user group (est=-1.05; *p*=0.05).

Table 9: GBTM Diagnostics including Covariates

Group	Proportion in Group	Average Posterior Probability	Odds of Correct Classification
With Time-Stable Covariates only			
Group 1	0.45	0.986	83.71
Group 2	0.12	0.947	127.10
Group 3	0.12	0.949	143.72
Group 4	0.09	0.951	199.09
Group 5	0.08	0.947	217.61
Group 6	0.14	0.978	271.46
With Time-Varying Covariates only			
Group 1	0.23	0.881	24.89
Group 2	0.25	0.941	47.99
Group 3	0.14	0.967	175.69
Group 4	0.14	0.944	116.89
Group 5	0.09	0.942	156.22
Group 6	0.16	0.924	65.20
With Time-Stable and Time-Varying Covariates			
Group 1	0.42	0.973	49.83
Group 2	0.08	0.897	99.98
Group 3	0.13	0.949	123.95
Group 4	0.11	0.978	360.56
Group 5	0.10	0.965	244.77
Group 6	0.16	0.968	166.83

Six-Group Trajectories Incorporating Time-Varying Covariates

The time-varying covariates are included alone to identify how they influence the substance use trajectories during the six-months. Including the time-varying covariates markedly changes the trajectories, as compared to the models without any covariates and with the time-stable covariates only (Figure 13). The abstainer and low-moderate groups are nearly indiscernible from one another. The moderate-increasing user group reduces to

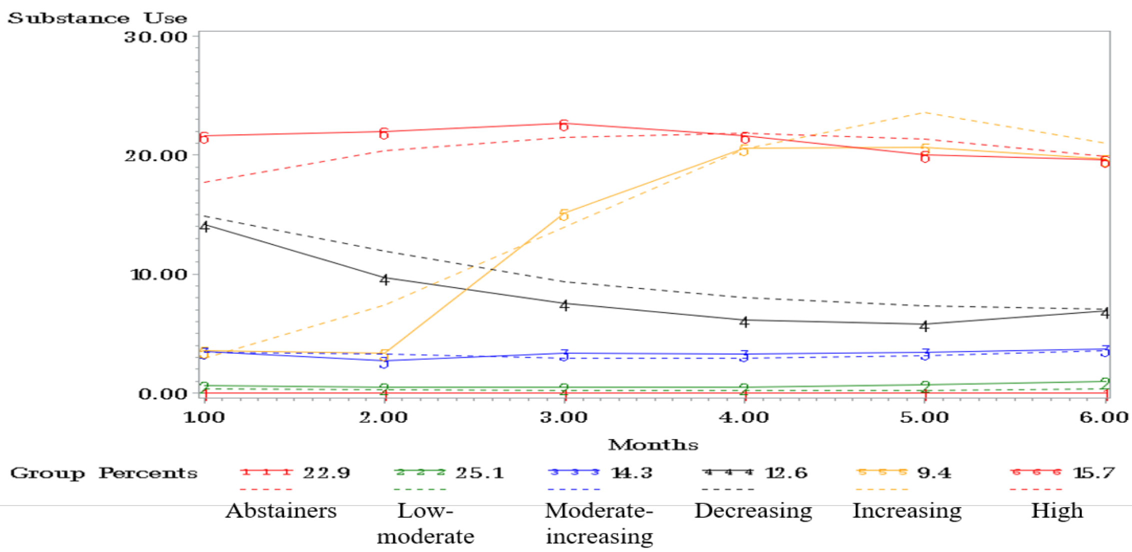


Figure 13: 6-Group Substance Use Trajectories with Time-Varying Covariates

be a low-moderate level of substance use. The decreasing group still exists, but it begins at a moderate-high rate of use, but then gradually declines instead of the steep reduction in previous models. The increasing and high user groups remain similar to previous models. The average posterior probabilities and OCC indicate that the model adequately assigns individuals to groups; however, it is evident in the group proportions that there was a large shift of cases out of the abstainers group and into the low-moderate group (Table 9). Table 10 demonstrates that 18.9% of the abstainers who changed groups between the time-stable model and time-varying model shifted to the low-moderate user group.

Table 10: Group Classification Comparing Models

Group Classification Change	No Covariates to Time-Stable Covariates	No Covariates to Time-Varying Covariates	No Covariates to Final Model	Time-Stable Covariates to Time-Varying Covariates	Time-Stable Covariates to Final Model	Time-Varying Covariates to Final Model
	N(%)	N(%)	N(%)	N(%)	N(%)	N(%)
No change	261 (94.9)	154 (56.0)	197 (71.6)	151 (54.9)	200 (72.7)	197 (71.6)
Abstainers to						
Low-moderate	1 (0.4)	**54 (19.6)**	4 (1.5)	**52 (18.9)**	4 (1.5)	--
Moderate-increasing	--	2 (0.7)	3 (1.1)	1 (0.4)	2 (0.7)	--
Decreasing	--	--	1 (0.4)	--	1 (0.4)	--
Low-moderate to						
Abstainer	1 (0.4)	--	1 (0.4)	--	--	**46 (16.7)**
Moderate-increasing	1 (0.4)	**24 (8.7)**	**20 (7.3)**	**25 (9.1)**	**21 (7.6)**	4 (1.5)
Increasing						1 (0.4)
Decreasing	--	3 (1.1)	1 (0.4)	2 (0.7)	1 (0.4)	1 (0.4)
Moderate-increasing to						
Low-moderate	1 (0.4)	--	6 (2.2)	--	6 (2.2)	9 (3.3)
Increasing	1 (0.4)	4 (1.5)	3 (1.1)	3 (1.1)	2 (0.7)	--
Decreasing	1 (0.4)	**18 (6.5)**	**14 (5.1)**	**17 (6.2)**	13 (4.7)	--
Increasing to						
Low-moderate	--	3 (1.1)	1 (0.4)	3 (1.1)	1 (0.4)	--
Moderate-increasing	--	--	1 (0.4)	--	1 (0.4)	1 (0.4)
High	--	1 (0.4)	1 (0.4)	1 (0.4)	1 (0.4)	--
Decreasing to						
Low-moderate						4 (1.5)
Moderate-increasing	--	1 (0.4)	2 (0.7)	1 (0.4)	2 (0.7)	2 (0.7)
Increasing	--	1 (0.4)	2 (0.7)	1 (0.4)	2 (0.7)	--
High	--	7 (2.5)	6 (2.2)	7 (2.5)	6 (2.2)	--
High to						
Increasing	--	1 (0.4)	1 (0.4)	1 (0.4)	1 (0.4)	1 (0.4)
Decreasing	--	2 (0.7)	3 (1.1)	2 (0.7)	3 (1.1)	1 (0.4)
Changed to missing	8 (2.9)	--	8 (2.9)	8 (2.9)	8 (2.9)	8 (2.9)

None of the time-varying covariates are statistically significant within the abstainers. Probation contacts are significantly associated with increases in substance use for the low-moderate (est=0.34; p<0.001), moderate-increasing (est=0.09; p<0.001), and decreasing (est=0.05; p=0.001) user groups. Formal treatment attendance is significantly associated with decreases in substance use for the moderate-increasing (est=-0.11; p<0.001), decreasing (est=-0.01; p=0.04), and increasing (est=-0.03; p<0.001) user groups. Within the moderate-increasing (est=1.02; p<0.001) and decreasing (est=0.27; p=0.03) user groups, the number of arrests is significantly associated with increases in substance use. Housing in a non-controlled environment during the six months following baseline is significantly associated with increases in substance use among the decreasing (est=0.08; p<0.001) and high (est=0.04; p<0.001) user groups.

Six-Group Trajectories Incorporating Time-Stable and Time-Varying Covariates

Including the time-stable and time-varying covariates revealed a trajectory model similar to that of the model with time-stable covariates only (Figure 14). The abstainer, increasing, and high user groups are nearly identical to the model including only the time-stable predictor variables, while the decreasing, low-moderate, and moderate-increasing user groups differ slightly. The decreasing group is still definable as decreasing use over time, but the decline is not as drastic as the time-stable model. The low-moderate group now begins at the same use as the abstainers, but gradually increases until month six when it drastically increases; the reason why the name is changing to "late-increasing." The moderate-increasing group remains steadily at a low-moderate level of use until month six when it gradually decreases; the reason why the name is changing to "low-moderate."

The average posterior probabilities and OCC indicate that the model adequately assigns individuals to groups (Table 9). Comparing the group classifications between the model with no covariates and the model with time-stable and time-varying covariates, the changing group proportions is largely due to 9.1% of individuals moving from the late-increasing/low-moderate group to the moderate-increasing/low-moderate group, as well as the moderate-increasing/low-moderate group changing to the decreasing group (6.2%). The group proportion change between the time-varying covariates model and the time-stable and time-varying covariates model is due to 16.7% of individuals moving from the moderate-increasing/low-moderate user group to abstainer group (Table 10). The final model including both time-stable and time-varying covariates is chosen as the best model given the meaningful separation of the abstainer and late-increasing user groups. Additionally, this model was an improvement over a five-group model because of the meaningful identification of a high-level use group within the six-group model (see Appendix D).

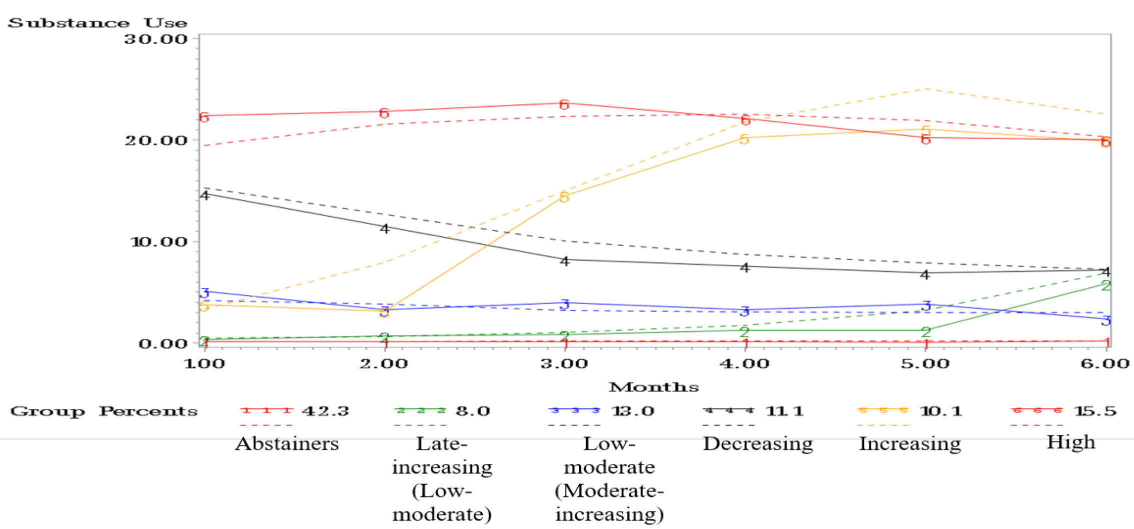


Figure 14: 6-Group Substance Use Trajectories with Time-Stable and Time-Varying Covariates

In the final model, the abstainer group displays no substance use. The late-increasing user group starts at the same level as the abstainer group, but increases slightly across time with a drastic increase in month six. The low-moderate maintains a low-moderate level of use with a slight increase at month six. The decreasing user group begin using at moderate level, but decrease use until month three when they level off. The increasing user group uses at a lower level until month two and then they increase use drastically until leveling off at month four. The high user group maintains a high level of use throughout the six months.

The abstainer group serves as the reference group in the time-stable results. No time-stable covariates are significant for the late-increasing group. For the low-moderate (est= 0.11; p= 0.01) and increasing (est=0.16; p=0.002) user groups, reporting higher risk taking significantly puts these individuals at risk of being in these respective groups with greater substance use as compared to the abstainer group. Family and peer drug use is a risk factor for the decreasing (est= 0.68; p= 0.05) and high (est=0.75; p=0.02) user groups. For the increasing user group, initiating substance use under the age of 16 is a risk factor (est=1.74; p=0.02). For the high user group, a more severe drug disorder is a risk factor (est=5.00; p=0.03). None of the time-varying covariates are significant for abstainer group. Probation contacts are significantly associated with decreases in substance use for the late-increasing user group (est= -0.24; p= 0.05), but significantly associated with increases in substance use for low-moderate (est=0.09; p<0.001) and decreasing (est=0.06; p<0.001) user groups. Formal treatment attendance is significantly associated with decreases in substance use for the low-moderate (est=-0.03; p<0.001), decreasing (est=-0.01; p=0.002), increasing (est=-0.03; p<0.001), and high (est=-0.00; p=0.05) user groups. Within the late-increasing (est= 1.06; p<0.001) and low-moderate (est=0.84; p=0.0001) user groups, the number of arrests is significantly associated with increases in substance use. Housing in a non-controlled environment during the six months following baseline is significantly associated with increases in substance use among the low-moderate (est=0.024; p=0.03), decreasing (est=0.11; p<0.001), increasing (est= 0.05; p= 0.003), and high (est=0.04; p<0.001) user groups.

Phase Three: Predictors of Re-arrest

Bivariate statistics for all of the time-stable independent variables are presented in Table 11. Females ($X^2(1, N = 275) = 8.65, p = .003$), those who used hard drugs ($X^2(1, N = 275) = 3.77, p = .05$), and those who reported more consequences from substance use ($F(1, 273)=4.48, p=.04$) are less likely to have been arrested. Those with more social support are less likely to be arrested ($F(1, 273)=6.09, p=.01$). Risk score fell just outside of significance. The substance use trajectories are not significant in the bivariate analyses.

The logistic regression with only the substance use trajectories has a pseudo R^2 of 1% (Table 12). Within this model, none of the substance use groups significantly predict re-arrest. The logistic regression including the time-stable independent variables that are not incorporated into the substance use trajectory groups has a pseudo R^2 of 20% and is not significant overall (p=0.06) (Table 13). In this regression, none of the substance use groups significantly predicts re-arrest. This model shows that females and those with more social support are less likely to be re-arrested. The logistic regression including the all of the time-stable independent variables, including those that are incorporated into the

Table 11: Bivariate Statistics for Predictors by Re-arrest

Predictor	Re-arrested N(%)/M±SD	Not re-arrested N(%)/M±SD	P-value
Demographics			
Female	**10 (15.9)**	**75 (35.4)**	**.003**
Nonwhite	52 (82.5)	162 (76.8)	.332
Stable housing	46 (73.0)	168 (79.2)	.296
High school diploma	19 (30.2)	86 (40.6)	.135
Committed relationship	36 (57.1)	118 (55.7)	.835
Unemployed	33 (52.4)	114 (53.8)	.846
Age	33.8 ± 11.1	35.0 ± 11.7	.445
Prior substance treatment and use history			
Lifetime prior treatment	30 (47.6)	106 (50.0)	.740
Initiated 15 and under	45 (71.4)	133 (62.7)	.205
Hard drug use	**26 (41.3)**	**117 (55.2)**	**.052**
Recent IV drug user	5 (7.9)	19 (9.0)	.800
Consequences of use	**18.4 ± 12.9**	**14.7 ± 12.1**	**.035**
Family/peer drug use	1.8 ± 0.8	1.8 ± 0.7	.732
ASI alcohol severity	0.2 ± 0.1	0.2 ± 0.2	.307
ASI drug severity	0.1 ± 0.1	0.1 ± 0.1	.651
Criminal justice			
Drug testing condition	45 (71.4)	155 (73.1)	.792
Drug treatment condition	18 (28.6)	81 (38.2)	.162
Drug instant offense	24 (38.1)	97 (45.8)	.282
Risk score	4.7 ± 2.0	4.2 ± 2.1	.064
Probation sentence	31.0 ± 22.6	33.3 ± 75.8	.814
Days on probation	37.3 ± 150.7	58.1 ± 246.9	.527
Psychosocial			
Risk mental disorders	11 (17.5)	21 (10.0)	.103
Risk severe mental disorder.	24 (38.1)	79 (37.4)	.925
Self-esteem	34.6 ± 8.3	35.6 ± 7.8	.388
Decision-making	36.5 ± 4.8	37.1 ± 4.9	.344
Hostility	27.2 ± 6.2	26.6 ± 7.0	.533
Risk taking	28.6 ± 6.3	28.4 ± 6.3	.778
Recognition	28.2 ± 9.0	27.7 ± 9.4	.681
Social support	**3.5 ± 1.1**	**3.9 ± 1.0**	**.014**
Self-determination	3.7 ± 0.8	3.8 ± 0.8	.145
Additional controls			
MI	20 (31.7)	68 (32.1)	.961
MAPIT	23 (36.5)	71 (33.5)	.658
Dallas	37 (58.7)	130 (61.3)	.712
Trajectory Group Classifications			
Abstainers *(reference category)*	25 (41.7)	90 (43.5)	.803
Late-increasing	4 (6.7)	17 (8.2)	.695
Low-moderate	6 (10.0)	29 (14.0)	.418
Decreasing	8 (13.3)	21 (10.1)	.485
Increasing	8 (13.3)	18 (8.7)	.286
High	9 (15.0)	32 (15.5)	.931

Table 12: Logistic Regression for Re-arrest with Substance Use Trajectories (n=267)

	B	S.E.	Wald	p	Exp(B)
Late increasing	-.166	.600	.077	.782	.847
Low-moderate	-.295	.502	.344	.557	.745
Decreasing	.316	.473	.446	.504	1.371
Increasing	.470	.481	.954	.329	1.600
High	.012	.440	.001	.977	1.012
Constant	-1.281	.226	32.102	.000	.278
Model X^2 =	2.164 p=.826				
Pseudo R^2 =	.012				

Table 13: Logistic Regression for Re-arrest with Substance Use Trajectories and Bivariate Independent Variables Not Included in Trajectories (n=264)

	B	S.E.	Wald	p	Exp(B)
Trajectory Group Classifications					
Late increasing	.023	.662	.001	.972	1.024
Low-moderate	-.364	.551	.436	.509	.695
Decreasing	.456	.539	.717	.397	1.578
Increasing	.652	.578	1.275	.259	1.920
High	-.097	.503	.037	.848	.908
Demographics					
Female	**-.926**	**.424**	**4.763**	**.029**	**.396**
Nonwhite	.514	.461	1.245	.264	1.672
High school diploma	-.298	.355	.707	.400	.742
Committed relationship	.357	.357	1.004	.316	1.430
Unemployed	-.299	.345	.753	.385	.741
Age	-.008	.016	.232	.630	.992
Prior substance treatment and use history					
Hard drug use	-.542	.388	1.956	.162	.581
Recent IV drug user	.219	.625	.123	.726	1.245
ASI alcohol severity	-1.416	1.286	1.212	.271	.243
Criminal justice					
Drug treatment condition	-.327	.379	.742	.389	.721
Drug instant offense	.228	.374	.374	.541	1.257
Risk score	.128	.091	1.969	.161	1.137
Probation sentence	-.001	.003	.073	.788	.999
Days on probation	-.008	.006	1.708	.191	.992
Psychosocial					
Risk mental disorders	.616	.493	1.557	.212	1.851
Risk severe mental disorder.	-.357	.393	.826	.363	.700
Decision-making	-.057	.036	2.590	.108	.944
Social support	**-.419**	**.181**	**5.388**	**.020**	**.658**
Additional controls					
MI	-.162	.414	.153	.695	.851
MAPIT	.046	.413	.013	.911	1.047
Constant	2.812	1.685	2.785	.095	16.647
Model X^2 =	36.618 p=.063				
Pseudo R^2 =	.197				

Table 14: Logistic Regression for Re-arrest with Substance Use Trajectories (n=264)

	B	S.E.	Wald	*p*	Exp(B)
Trajectory Group Classifications					
Late increasing	-.015	.705	.000	.984	.986
Low-moderate	-.535	.625	.612	.392	.585
Decreasing	.480	.611	.030	.432	1.616
Increasing	.644	.670	1.75	.336	1.904
High	-.351	.553	.088	.525	.704
Demographics					
Female	**-.901**	**.456**	**3.897**	**.048**	**.406**
Nonwhite	.502	.527	.907	.341	1.652
Stable housing	.027	.479	.003	.956	1.027
High school diploma	-.326	.375	.757	.384	.722
Committed relationship	.412	.376	1.203	.273	1.510
Unemployed	-.187	.370	.255	.613	.829
Age	-.008	.020	.163	.686	.992
Prior substance treatment and use history					
Lifetime prior treatment	-.403	.461	.765	.382	.668
Initiated 15 and under	.195	.404	.233	.629	1.215
Hard drug use	-.749	.442	2.872	.090	.473
Recent IV drug user	-.388	.702	.306	.580	.678
Consequences of use	**.051**	**.023**	**4.996**	**.025**	**1.052**
Family/peer drug use	-.037	.262	.020	.887	.963
ASI alcohol severity	-1.390	1.379	1.017	.313	.249
ASI drug severity	2.926	1.940	2.276	.131	18.657
Criminal justice					
Drug testing condition	.078	.465	.028	.866	1.082
Drug treatment condition	-.629	.435	2.088	.148	.533
Drug instant offense	-.016	.413	.002	.969	.984
Risk score	.137	.104	1.748	.186	1.147
Probation sentence	-.002	.004	.355	.551	.998
Days on probation	-.010	.008	1.674	.196	.990
Psychosocial					
Risk mental disorders	.728	.562	1.678	.195	2.070
Risk severe mental disorder.	-.304	.444	.469	.493	.738
Self-esteem	.033	.034	.964	.326	1.033
Decision-making	-.064	.044	2.124	.145	.938
Hostility	-.046	.036	1.590	.207	.955
Risk taking	-.019	.034	.297	.586	.982
Recognition	.000	.034	.000	.999	1.000
Social support	**-.487**	**.214**	**5.197**	**.023**	**.615**
Self-determination	-.012	.274	.002	.966	.988
Additional controls					
MI	-.339	.442	.589	.443	.712
MAPIT	.063	.434	.021	.885	1.065
Dallas	.402	.509	.624	.430	1.494
Constant	2.951	2.959	.994	.319	19.121
Model X^2 =	49.254 p=.104				
Pseudo R^2 =	.259				

substance use trajectory groups has a pseudo R^2 of 26% and is not significant overall (*p*=0.10) (Table 14). Just as in the previous model, females and those with more social support are less likely to be re-arrested. Additionally, in this model, those who experienced more consequences from their substance use are more likely to be re-arrested.

The survival analysis including only the substance use trajectory groups is not significant overall (p=.87), meaning that this model is not an improvement relative to null. In the model including only the substance use trajectory groups, none of the groups significantly predicts the number of days until re-arrest (Table 15). Examining the survival functions, the increasing and decreasing groups have the shortest survival times (Figure 15). The abstainer and high user groups have the same number of days to re-arrest, while the late-increasing and low-moderate groups are similar and have the longest survival times.

Table 15: Cox Proportional Hazards Model with Substance Use Trajectories (n=267)

	B	SE	p	Exp(B)	95% CI
Late-increasing	-.138	.539	.798	.872	.303, 2.504
Low-moderate	-.251	.455	.581	.778	.319, 1.897
Decreasing	.286	.406	.482	1.331	.600, 2.950
Increasing	.337	.406	.407	1.400	.632, 3.105
High	.036	.389	.926	1.037	.484, 2.221
-2 Log Likelihood	654.297				
Model X^2 =	1.819 p=.874				

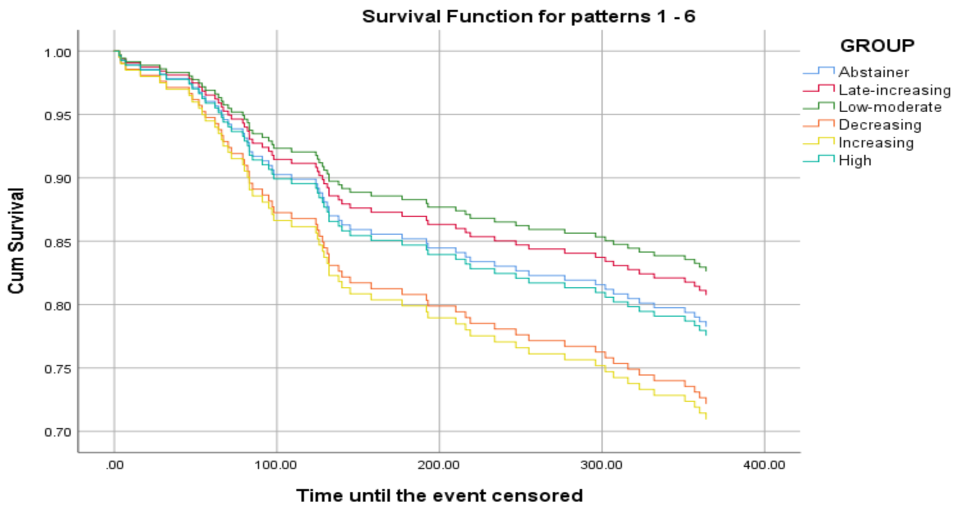


Figure 15: Survival Function with Substance Use Trajectories Groups Only

Table 16 presents the results of the survival model with the time-stable covariates not incorporated into the substance use trajectory groups included. The omnibus test showed that this model was not significant overall (*p*=0.08), again meaning that this model provides no improvement in comparison to null. None of the substance use trajectory groups significantly predicts the number of days until re-arrest. The only significant covariate is gender. Being female leads to having a longer survival time as compared to males (B = -0.775, p = 0.04, HR = 0.461). Looking at the survival function, the increasing and decreasing user groups have the shortest number of days to re-arrest (Figure 16), just as the model with only the substance use trajectory groups. The abstainer and high user groups are still similar, but slightly longer survival than in the previous model. The late-increasing user group is still a similar to the previous model, but is now more similar to the abstainer and high user groups' survival times. The low-moderate user group has the longest survival time to re-arrest.

Table 16: Cox Proportional Hazards Model with Substance Use Trajectories (n=264)

	B	SE	*p*	Exp(B)	95% CI	
Trajectory Group Classifications						
Late increasing	.132	.560	.813	1.141	.381	3.418
Low-moderate	-.321	.477	.501	.725	.285	1.849
Decreasing	.517	.455	.256	1.677	.687	4.094
Increasing	.433	.438	.323	1.541	.653	3.637
High	-.064	.422	.880	.938	.410	2.147
Demographics						
Female	**-.775**	**.371**	**.037**	**.461**	**.223**	**.953**
Nonwhite	.358	.402	.373	1.431	.651	3.145
High school diploma	-.221	.301	.462	.801	.444	1.445
Committed relationship	.214	.293	.466	1.238	.697	2.200
Unemployed	-.215	.290	.458	.806	.457	1.424
Age	-.009	.014	.491	.991	.964	1.018
Prior substance treatment and use history						
Hard drug use	-.484	.329	.141	.616	.323	1.175
Recent IV drug user	.082	.537	.879	1.085	.379	3.110
ASI alcohol severity	-1.251	1.074	.244	.286	.035	2.350
Criminal justice						
Drug treatment condition	-.291	.322	.366	.748	.398	1.404
Drug instant offense	.212	.309	.493	1.236	.675	2.263
Risk score	.139	.077	.070	1.149	.989	1.336
Probation sentence	-.001	.003	.769	.999	.994	1.004
Days on probation	-.006	.005	.207	.994	.985	1.003
Psychosocial						
Risk mental disorders	.558	.404	.167	1.747	.792	3.854
Risk severe mental disorder.	-.259	.326	.426	.772	.407	1.461
Decision-making	-.051	.029	.078	.951	.898	1.006
Social support	-.269	.140	.055	.764	.580	1.006
Additional controls						
MI	-.086	.341	.802	.918	.471	1.790
MAPIT	.179	.338	.597	1.196	.616	2.321
-2 Log Likelihood	619.200					
Model X^2 =	35.383 p=.082					

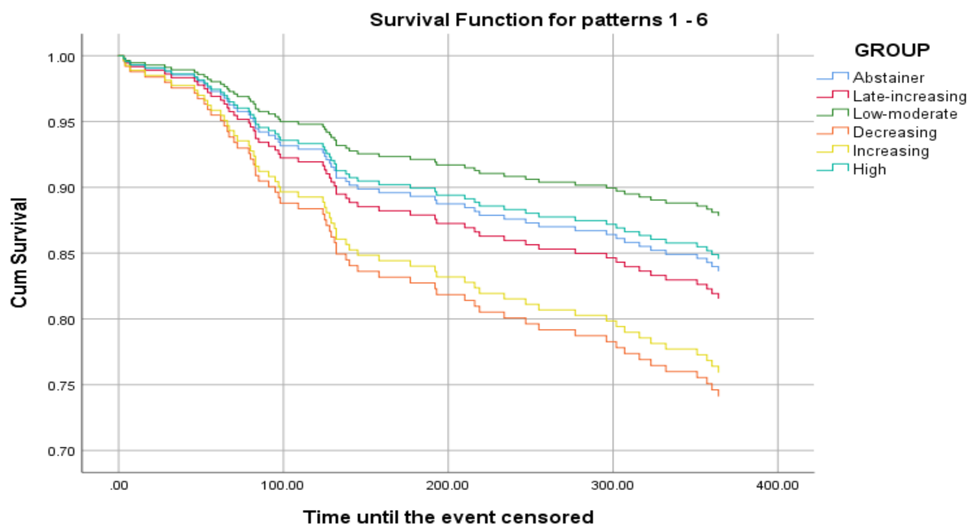


Figure 16: Survival Function with Substance Use Trajectories and Time-Stable Independent Variables Not Incorporated in Trajectory Groups

Next, survival analysis examines the time to re-arrest while including all of the time-stable covariates along with the substance use trajectory groups (Table 17). Again, the omnibus test showed that this model was not significant overall (p=0.11). None of the substance use trajectory groups significantly predicts the number of days until re-arrest. However, being a hard drug user, the consequences of substance use experienced, and risk score are significant. Being a hard drug user leads to having a longer survival time (B = -0.748, p = 0.04, HR = 0.474). Having experienced greater consequences for their substance use (B = 0.046, p = 0.01, HR = 1.047) and having a higher risk score (B = .167, p = 0.05, HR = 1.182) have a shorter survival time to re-arrest. As with the two previous survival functions, the decreasing user group has the shortest number of days to re-arrest (Figure 17). The increasing user group demonstrates similar failure rates as before, but this is now more similar to the late-increasing and abstainer group. The low-moderate and higher user groups have the longest survival time to re-arrest.

Table 17: Cox Proportional Hazards Model with Substance Use Trajectories and all Time-Stable Independent Variables (n=264)

	B	SE	*p*	Exp(B)	95% CI	
Trajectory Group Classifications						
Late increasing	.085	.593	.885	1.089	.341	3.481
Low-moderate	-.420	.526	.425	.657	.235	1.842
Decreasing	.633	.496	.202	1.884	.713	4.978
Increasing	.313	.501	.532	1.368	.513	3.650
High	-.351	.476	.462	.704	.277	1.792
Demographics						
Female	-.691	.392	.078	.501	.233	1.080
Nonwhite	.323	.452	.475	1.381	.569	3.351
Stable housing	.151	.394	.702	1.163	.537	2.520
High school diploma	-.237	.311	.445	.789	.429	1.451
Committed relationship	.247	.312	.428	1.280	.695	2.358
Unemployed	-.128	.315	.683	.880	.475	1.630
Age	-.009	.017	.613	.991	.959	1.025
Prior substance treatment and use history						
Lifetime prior treatment	-.467	.390	.231	.627	.292	1.347
Initiated 15 and under	.116	.349	.739	1.123	.567	2.227
Hard drug use	**-.748**	**.371**	**.044**	**.474**	**.229**	**.979**
Recent IV drug user	-.501	.622	.421	.606	.179	2.051
Consequences of use	**.046**	**.018**	**.010**	**1.047**	**1.011**	**1.085**
Family/peer drug use	-.018	.208	.931	.982	.653	1.477
ASI alcohol severity	-1.225	1.137	.281	.294	.032	2.729
ASI drug severity	2.016	1.699	.235	7.512	.269	209.693
Criminal justice						
Drug testing condition	.159	.387	.682	1.172	.549	2.501
Drug treatment condition	-.456	.363	.210	.634	.311	1.292
Drug instant offense	-.025	.339	.941	.975	.502	1.895
Risk score	**.167**	**.087**	**.053**	**1.182**	**.998**	**1.401**
Probation sentence	-.002	.003	.464	.998	.992	1.004
Days on probation	-.006	.005	.227	.994	.983	1.004
Psychosocial						
Risk mental disorders	.489	.459	.287	1.630	.663	4.008
Risk severe mental disorder.	-.356	.367	.332	.701	.341	1.438
Self-esteem	.025	.027	.363	1.025	.972	1.082
Decision-making	-.044	.035	.209	.957	.894	1.025
Hostility	-.038	.030	.208	.963	.908	1.021
Risk taking	-.006	.028	.840	.994	.941	1.051
Recognition	.003	.028	.919	1.003	.950	1.058
Social support	-.272	.163	.095	.762	.554	1.049
Self-determination	-.125	.226	.579	.882	.567	1.373
Additional controls						
MI	-.201	.355	.571	.818	.408	1.640
MAPIT	.176	.352	.617	1.193	.598	2.378
Dallas	.147	.417	.725	1.158	.511	2.624
-2 Log Likelihood	605.872					
Model X^2 =	48.710 p=.114					

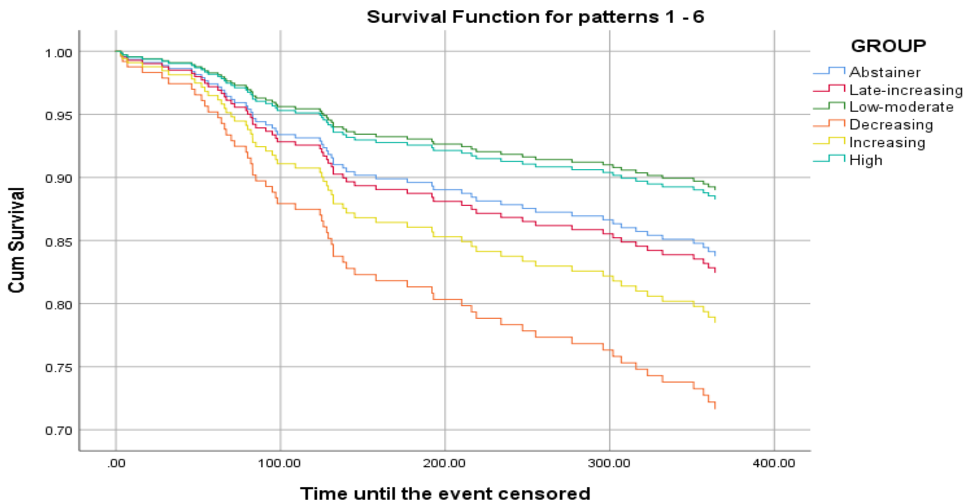


Figure 17: Survival Function with Substance Use Trajectories and All Time-Stable Independent Variables

CHAPTER SIX: DISCUSSION AND CONCLUSIONS

Discussion

The current study examines the substance use patterns among individuals while on community supervision, with attention to the factors that predict membership into those substance use groups and how those substance use groups may predict re-arrest. Similar to prior research examining substance use groups, the current study found distinct groups of substance users (Caudy et al., 2014; Chou et al., 2003; Hser, Huang, et al. 2007; Hser et al., 2008; Kertesz et al., 2012; Teesson et al., 2017). Six groups of substance users emerged from the data: abstainers, late-increasing, low-moderate, increasing, decreasing, and high user groups. The abstainer group reports no substance use behaviors. The late-increasing user group starts at the same level as the abstainer group, but increases slightly across time with a drastic increase in month six. The low-moderate reports a low-moderate level of use with a slight increase at month six. The decreasing user group reports that they are moderate users at the baseline assessment, but decrease use until month three when they level off. The increasing user group reports use at a lower level until month two and then they increase use drastically until leveling off at month four. The high user group reports a high level of use throughout the six months.

The findings of this study cannot be directly compared to other studies due to the follow-up time and sample differences; however, there are similarities that support the validity of the current findings. In prior research, it is common to find both high stable users and low/non-users (Caudy et al., 2014; Hser, Huang, et al., 2007; Hser et al., 2008; Teesson et al., 2017). Furthermore, in Caudy and colleagues (2014), the study with the closest sample and design, the patterns of gradual declining aligns with this studies' decreasing user group. Two of the groups in the current study demonstrated increasing use. Teesson and colleagues (2017) study of heroin users over a 10-year follow-up had this finding. Finding increasing patterns of use in such a short time period may be due to a large portion of the sample being new to probation and having made recent changes to their substance use behaviors prior to the examined time period. Another study found that substance use increases as the time from prison release increases (Chamberlain et al., 2019). The authors suggest that at prison release, individuals use substances less due to increased motivation and confidence about changing their substance using behaviors, but that challenges and distress post-release lead to increases in substance use as time goes on. Given that nearly 80 percent of the current study's sample had been on probation for less than 30 days, it is possible that a similar increasing pattern from start of probation is responsible for the increasing patterns found. Future research is needed to examine how initiating probation may effect individuals' patterns of substance use. This will generate a better understanding of how initiating probation can potentially deter substance use.

Both time-varying and time-stable variables are significantly related to the final group membership. Group membership has a significant relationship with the number of probation contacts and arrests for three groups: late-increasing, low-moderate, and decreasing user groups. Probation contacts are associated with decreased use in the late-increasing group, but associated with increased use in the low-moderate and decreasing user groups. For the late-increasing and low-moderate user groups, the number of arrests are associated with increased substance use. The mixed findings for these time-varying criminal justice variables most likely reflect the complicated relationship between substance use and criminal justice involvement, which is likely to be affected by the drug(s) of choice and lifetime use factors (Hakansson & Berglund, 2012). In a recent study, Green and colleagues (2019) found a reciprocal relationship between arrest and substance use for African-Americans, demonstrating the complexity of substance use behaviors when interacting with formal criminal justice practices; disproportionate contact with the criminal justice system affects these patterns. The relationship between arrest and probation contacts with three substance using groups may be tapping into a complex interaction that needs to be contextualized further. These complex relationships need further exploring, particularly regarding the impact of the disproportionate contact with the criminal justice system.

Furthermore, formal treatment and housing in a non-controlled environment has a significant relationship with the low-moderate, decreasing, increasing, and high user groups. As would be expected, formal treatment is related to decreased use for all of these groups, while days in a non-controlled environment is associated with increases in use for these groups. Given the high prevalence of outpatient substance abuse treatment options (i.e., in the community), with much fewer residential or controlled setting treatment options available, this battling dichotomy between the risk of being in the community and the protection of a formal treatment environment should be given more attention. This demonstrates the importance of ensuring that formal treatment environments in the community are protected, positive places for people to work on their substance use. Spohr's (2017) finding that probationer's with better quality social support and positive interactions were less likely to continue using substances on probation supports this. Further, as Spohr (2017) suggests, it could be that treatment could provide a support for abstinence when otherwise the individual has increased negative social supports and interactions in their life.

Increased risk taking behavior is associated with increased likelihood of being in the low-moderate and increasing user groups as compared to the abstainers. The increased risk taking behavior may reflect those willing to risk sustained minimal substance use for the duration of supervision. Furthermore, the increasing group drastically rises at month two, which may reflect a time period during early supervision when an individuals' assumed risk of being caught using substances may change. Perhaps, after two months they became accustomed to the community supervision expectations and determined that the risk of being caught was low, leading to justifications for increased substance use. Individuals reporting family and peer drug use are at higher risk of being in the decreasing and high user groups. The finding that family and peer substance use is related to both a decreasing use pattern and a stably high use pattern is interesting, but similar to findings Spohr (2017) found examining this study sample. Spohr (2017) found improved social support quality and positive interactions were related to being abstinent, while poorer social support quality and negative interactions were related to increased treatment initiation. The family and peer drug use items in this study overlaps with Spohr's (2017) measure of negative interactions. Just as Spohr (2017) found, this study's finding suggests that negative interactions (i.e., family and peer substance use) may motivate individuals to seek out an alternative to substance use (e.g., treatment) that would promote more positive interactions, therefore decreasing their use. On the other hand, these same negative interactions may support continued high substance use even when it could result in negative outcomes on probation. More research is needed to examine how social interaction quality may relate to individuals substance use patterns over time and engagement with positive factors such as treatment.

Those who reported initiating substance use under the age of 16 are at higher risk to be in the increasing group, while those with more severe drug use disorders are more likely to be in the high user group. Prior research supports these findings about the patterns of continued substance use due to prevalence of family and peer substance use, initiation of substances under 16, and severe substance use disorders (Caudy et al., 2014; Hser, Huang, et al., 2007; Hser et al., 2008; Kertesz et al., 2012; O'Donnell et al., 2018).

Examining these factors related to group membership, there is a similarity that stands out. While risk taking is an internal factor that predicts membership to two groups, most of the related factors are external to the individual. They represent environmental, social, or other system factors that are arguably within limited control of the individual and can simultaneously serve as a positive and negative influence on substance use. For instance, relationships with family and peers who use substances can be complicated and often the only control the individual can exert is how often they directly interact with a person. These relationships can serve as both a positive influence to reduce substance use or a negative influence to reinforce and support the behavior. Even the ability of probation to affect substance use is complicated as seen in the finding that probation contacts increase use among the low-moderate group and decrease use in the late-increasing group. The most notable factor is formal treatment decreasing substance use in four groups, three of which display particularly troubling use patterns for those on community supervision (i.e., low-moderate, increasing, high). We need to have a better understanding of how these external factors interact with one another and individuals' characteristics to help support individuals moving from a high trajectory of use to decreasing.

Despite the value of understanding the different substance use trajectories, these groups failed to predict re-arrest and time until re-arrest. However, a few variables predicted re-arrest. As expected, females and those with more social support are less likely to be re-arrested. These findings align with prior research findings (De Li et al., 2000; Huebner & Cobbina, 2007; Wilson et al., 2018). However, both the current study and Spohr (2017) found that quantity of social support was not related to substance use. The finding that quantity of social support is related to re-arrest supports the need for further research to examine how different aspects of social support may differentially impact criminal justice and health behavior outcomes. Additionally, those who experienced more consequences from their substance use are more likely to be re-arrested. The consequences of substance use also emerges in the survival analysis, with those that experienced greater consequences having the shortest survival time to re-arrest. This finding is not surprising given that one of the consequences they likely experienced was their arrest. Hard drug users have a longer survival time and those with a higher risk score have a shorter survival time. Those with a higher risk score being arrested more quickly is not surprising since probation agencies typically adjust the amount of monitoring for different risk levels, with those at higher risk reporting more often and with more conditions such as drug testing. This introduces more opportunities for re-arrest to happen for these individuals.

Surprisingly, the finding that hard drug users have a longer time to re-arrest is contradictory to what would be expected. One reason may be how the criminal justice system responds to hard drug use. For instance, in Baltimore, there are designated treatment slots made available to those who have more severe substance dependence (i.e., likely hard drug users) and sending individuals to treatment would be the initial response to a failed drug test. Arrest for a probation violation is not likely to occur. This policy of using treatment as a response may extend time to failure for hard drug users, or even improve the likelihood of individuals succeeding on supervision (Boman et al., 2019).

Theoretical Implications

As discussed by Best and colleagues (2017), the theories of criminal desistance and substance use recovery have many similarities, including substantial overlap in the impacted individuals. Furthermore, Best and colleagues (2017) note, "relatively little attention has been paid to the impact of desisting from one behavior on stopping the other" (pg. 1). The current study begins exploring this gap in understanding how different substance use patterns relate to re-arrest. Despite not finding these substance use patterns to predict re-arrest, this study's findings support some of the theoretical overlaps in desistance from both substance use and criminal involvement. The current findings suggest the need for further research to understand how desistance from substance use and criminal behavior interact.

Unifying themes for theories of desistance and recovery include the importance of identity and social capital (Best et al., 2017). The current study found that family and peer substance use played a significant role as a risk factor for continued substance use patterns. Additionally, higher social support consistently predicted a reduced likelihood of re-arrest. These findings support the importance of social capital for both substance use recover and criminal desistance. However, as discussed previously, this raises interesting questions about the differing roles of quantity versus quality of social support. The current study supports previous findings from Spohr (2017) regarding an aspect of social support quality influencing substance use behaviors, but this study's findings also supports the potential importance of quantity of social support when predicting future criminal justice involvement. Future research needs to examine how types of social capital can interact and influence the desistance process from both substance use and criminal behavior in both the short- and long-term.

Theories of desistance and recovery both support that there are stages to the process, but that determining what predicts an individual's path through the process is challenging (Best et al., 2017). The current research provides some evidence that the criminal justice system plays a role in the recovery process, but that there is much more to learn. These findings suggest that distinct patterns of use exist in the short-term for people under community supervision and that how supervision is conducted (e.g., probation contacts) plays a part to impact these patterns. Life course theory suggests that events known as turning points can intercede in substance use behaviors and criminal desistance (Elder, 1994; Hser et al., 2007; Laub & Sampson, 1993). The current study supports that even in a short window of time, community supervision may be behaving as a turning point for some individuals. Future research should focus more on how community supervision plays a role in desistance from substance use and criminal behavior.

Practice and Policy Implications

Despite the lack of connection between the substance use trajectories and re-arrest found in this study, there are practical implications to help guide how the criminal justice system, especially community supervision, handles substance use. This sample consists of individuals with relatively low alcohol and drug use severities, which may be why nearly half of the sample falls into an abstainer group. This suggests that for many individuals probation may be a deterrent to substance use, at least in the short-term. However, this also means that more than half of the sample continued substance use in some manner, despite the potential negative consequences of use behaviors while being monitored. This provides insight into changing how the criminal justice system handles identifying and addressing the needs of individuals on community supervision. In the criminal justice system, there tends to be a heavy focus on individuals who clearly present as high risk (generally driven by historical criminal justice factors) and/or with criminogenic factors such as severe substance use disorder. However, this can lead to little treatment attention given to individuals who do not meet a certain threshold of criminogenic need (e.g., substance use severity) or risk level. Research suggests that many of these individuals could have a complex combination of needs and destabilizers that make them more likely to recidivate (Taxman & Caudy, 2015). In particular, these trajectories of continued substance use (likely identified as a low or moderate problem use behavior) may be indicative of those who need programming focused on their lifestyle choices. The attention to lifestyle choices may include recreational substance use, peers, criminal behavior, and potentially an overwhelming multitude of destabilizers. In community supervision offices, staff should focus holistically on an individual to address all their needs and not only target substance use behaviors that are more easily monitored. Future research should explore the needs of individuals who may be on the cusp of more severe substance use disorders and how community supervision could more proactively intervene.

The substance use groups that emerged can inform probation officers when they should be looking for signs of changing substance use patterns. Around the two-month time, the increasing group drastically increased their use and the decreasing group showed their first indications of reduced use. Prior research demonstrates that individuals are at the greatest risk of recidivism during the first few months of community supervision (Byrne, 2009). This study supports that the first few months are also crucial to identifying key substance use changes, whether positive or negative. Considering those who demonstrate little to no substance use early on supervision, only to reach continuously high levels of use within a few months (i.e., late-increasing, increasing), probation officers should consider random drug testing and face-to-face visits throughout at least the first six months of probation to proactively address treatment needs with those who quickly escalate their substance use.

The finding that formal treatment was a protective factor within many of the substance use trajectories supports the importance of engaging individuals in formal treatment when needed. The short time frame demonstrates the importance of getting people into treatment quickly. This means overcoming the systematic challenges such as waitlists that exist to getting individuals in formal treatment in a timely manner. Community supervision agencies should leverage their resources to continue overcoming these systematic challenges. Additionally, another common challenge for treatment initiation among criminal justice involved individuals is engagement. In this aspect, community supervision can also play a significant role. Emerging research demonstrates innovative ways that community supervision and health care providers can work together to build treatment engagement. Looking at this same sample, Lerch and colleagues (2017) found that the computerized intervention MAPIT increased treatment initiation. In a feasibility study, Banta-Green and colleagues (2019) found that care navigators providing education and decision-making guidance about medication treatment for opioid use disorders for incarcerated individuals as they reentered the community greatly assisted. However, logistics with community supervision greatly impeded recruiting and studying this intervention fully. Both computerized interventions and navigators offer potential ways that community supervision could support individuals in a way that could positively impact individuals substance use patterns and engagement in formal treatment.

In 2013, the diagnostic criteria for substance use disorders changed with the DSM-V (Center for Behavioral Health Statistics and Quality, 2016). While the DSM-IV diagnosed individuals with either substance abuse or dependence, the DSM-V identifies an individual as having a substance use disorder with severity levels (i.e., mild, moderate, and severe). Examination of alcohol use disorder prevalence rate differences due to this diagnosis change demonstrate that using the DSM-V tends to identify more individuals with disorders (Bartoli et al., 2015; Takahashi et al., 2017). Among a Veterans Affair (VA) sample, those diagnosed by the DSM-V had fewer symptoms and lower readiness to change than when they also met the DSM-IV criteria (Takahashi et al., 2017). Given the potential changes in the individuals diagnosed with substance use disorders and how treatment is applied to different severity levels, the criminal justice system needs to be responsive to how they handle substance use among their population. The current finding of distinct substance use trajectories for those on community supervision could reflect differences in severity of substance use disorders, suggested by the significance of the ASI severity score for the high user group. More research is needed to understand how different patterns of substance use and substance use disorder diagnoses interact and the most effective ways for community supervision to positively influence outcomes. For instance, if family and peer substance use is a risk factor for certain patterns of substance use as suggested by the current study, as well as different substance use disorder severity levels, then community supervision policies should focus on how to best mitigate that risk factor.

Future Research

There is much more that needs to be understood about individuals who continue to use substances while under community supervision. Similar to prior research, the current study finds that there are few predictor variables of substance use behaviors. This is an area where research is needed to identify those individuals that are more likely to continue their substance use (Caudy et al., 2014; Teesson et al., 2017). In this study, the time-varying variables suggest that events co-occurring with substance use should be explored to assess how these variables impact substance using behavior. In particular, more research is needed to understand the role that the criminal justice factors such as probation contacts play in substance using behavior. As other researchers have demonstrated, the relationship between the criminal justice system and substance use is complicated and there is still much more to learn (Green et al., 2019; Schwalbe, 2019). Additionally, the housing in a non-controlled environment time-varying variable suggests that more needs to be understood about how housing plays a role in changing substance use patterns. There are many nuances to housing beyond only controlled versus non-controlled such as homelessness and living with family and friends that could influence substance use and that future research should be explored (Chamberlain et al., 2019; O'Donnell et al., 2018).

Future research should consider a bigger picture approach to the nexus of substance use behaviors and the criminal justice system. As Chamberlain and colleagues (2019) suggest, much of the research conducted so far examines populations of individuals actively using substances, but there needs to be more examination of samples that contain users and non-users, like this study. The current study began with a sample of individuals meeting a substance use criteria; however, the analysis reveals that this sample contains individuals with a lower level of alcohol and drug use severity that may be similar to non-users. Samples with a variety of users and non-users on community supervision needs to be examined in future research.

Additionally, future research should examine how individuals using harder substances are handled by the criminal justice system, especially in the current environment of the opioid epidemic. It may be that being a hard drug user as compared to using other substances could become a protective factor to delay recidivism within the criminal justice system. Future research should examine how substance use trajectories such those found here predict other outcomes beyond re-arrest. Prior researchers found that substance use trajectories were related to other outcomes such as health problems, treatment involvement, and housing stability (Caudy et al., 2014; Teesson et al., 2017).

Limitations

This study has several limitations. This study uses self-report data that could be influenced by participant factors such as memory loss or false information. Researchers verified information to every extent possible by cross-validating and verifying responses through audio recordings. For the current study, cases that could potentially be poor data are removed to help reduce data concerns. Additionally, this study only accounts for one measure of recidivism (i.e., re-arrest). The measure of re-arrest is biased in that it can over-count individuals in communities targeted more frequently by policing practices, as well as not accurately reflecting dispositions finding that actual criminal behavior occurred.

The current study is limited by the inclusion of those who were found eligible to participate in the original MAPIT study, and the measures and follow-up time designed for the original study's aims. Of the 2,307 people originally screened for MAPIT, only 783 met the eligibility criteria, and only 360 were randomized. This study's participants represent a limited sample of individuals on community supervision. Prior research helps provide validity to the current finings, but this study should be replicated with a larger, more varied sample of individuals on supervision to aid generalizability. It is possible that examining another population on community supervision and with more intentional measurements would reveal different findings. Examining variables such as how quality of relationships changed over time as opposed to relationship status at baseline may affect the findings (Moos, 2007; Tracy et al., 2005). Furthermore, this study is limited with a short follow-up to examine the concept of desistance. Most studies examining life course and desistance incorporate multiple years of follow-up to capture the process. With only a six-month follow-up, it is hard to argue that the process of desistance is occurring. However, this brief snapshot provides some indication that people are moving in the direction of desistance, and lays the foundation for future research with longer follow-up. Additionally, the sample size of this study is on the smaller side for the methodology used. The reduced power because of the sample size may have influenced the outcomes. Finally, the commonly used practice of only including one variable for every 10 cases was violated in the final models for both the logistic regression and Cox proportional hazards models. However, this guideline has been challenged by researchers suggesting that it should be relaxed (Vittinghoff & McCulloch, 2006), thus the researcher explores these models for the current study.

Conclusions

Probation is a deterrent to substance use during supervision for many individuals, but there are distinct substance use patterns that emerged from the data. Yet, the pattern of substance use during six months of supervision did not predict later re-arrest among this group of individuals on community supervision. The current study advances what we know about individuals using substances while under community supervision. These trajectory groups provide information about critical time frames where individuals are testing the probation waters, and provides fruitful information to develop probation policies. The patterns of substance use provide an interesting clustering of events that could support interventions and justice controls to serve both health and justice goals. Collectively, the justice and substance abuse nexus requires more research about how to affect success on community supervision, as well as the ultimate health and well-being of the individual.

APPENDIX A: DALLAS SAMPLE SENSITIVITY ANALYSIS

Within the 275 cases analyzed for the current study, 167 were Dallas cases. Of those 167 cases, 113 were recruited before the recruitment change and 54 were recruited after the recruitment change. The bivariate statistics comparing the sample between those recruited before and after the change revealed that the samples only differed on one factor, criminal justice risk score. The sample collected after the recruitment change had a significantly higher risk level ($F(1, 166)=5.93$, $p=0.16$). This significant difference is likely due to the risk level stratification and the focused recruitment toward high risk individuals in Dallas toward the end of the study. In other words, Dallas recruited their target number of low/moderate risk individuals earlier in the study recruitment and were focused on high-risk recruitment to balance the stratification during later recruitment.

Table 1: Dallas Recruitment Comparison on Time-Stable Predictor Variables (n=167)

Variables	Pre-Change (n=113) No.(%) or Mean ±SD	Post-Change (n=54) No.(%) or Mean ±SD
Demographics		
Age	31.2 ± 9.8	32.9 ± 9.8
Female	37 (32.7)	19 (35.2)
Nonwhite	79 (70.5)	35 (64.8)
Stable housing	94 (83.2)	48 (88.9)
High school diploma	53 (46.9)	20 (37.0)
Committed relationship	62 (54.9)	25 (46.3)
Unemployed	49 (43.4)	26 (48.1)
Prior Substance Treatment and Use History		
Consequences of use	14.4 ± 12.3	11.3 ± 10.8
Family/peer drug use	1.8 ± 0.7	1.7 ± 0.7
ASI alcohol severity	0.2 ± 0.2	0.3 ± 0.2
ASI drug severity	0.1 ± 0.1	0.1 ± 0.1
Lifetime prior treatment	41 (36.3)	21 (38.9)
Initiated use 15 and under	73 (64.6)	31 (57.4)
Hard drug use	48 (42.5)	27 (50.0)
Recent IV drug user	10 (8.8)	3 (5.6)
Criminal Justice		
Criminal justice static risk score*	3.5 ± 2.1	4.3 ± 1.9
Months sentenced to probation	33.73 ± 24.4	37.8 ± 18.5
Days on probation	87.0 ± 343.5	19.0 ± 14.9
Drug testing condition	98 (86.7)	52 (96.3)
Drug treatment condition	37 (32.7)	21 (38.9)
Drug instant offense	41 (36.3)	23 (42.6)
Psychosocial		
Self-esteem	34.9 ± 8.7	35.9 ± 7.0
Decision-making	37.2 ± 5.6	36.7 ± 4.5
Hostility	26.7 ± 6.9	25.3 ± 7.1
Risk taking	28.6 ± 6.8	28.1 ± 6.1
Recognition	26.2 ± 8.7	25.4 ± 8.5
Social support	3.8 ± 1.0	4.0 ± 0.9
Self-determination	3.9 ± 0.8	4.0 ± 0.7
Risk of mental disorders	11 (9.7)	2 (3.7)
Risk of severe mental disorders	46 (40.7)	16 (29.6)
Additional controls		
MI	36 (31.9)	15 (27.8)
MAPIT	37 (32.7)	19 (35.2)
SAU	40 (35.4)	20 (37.0)

* $p < .05$; ** $p < .01$; ***$p < .000$

APPENDIX B: MISSING DATA AND SAMPLE SELECTION

Identifying and Handling Missing Data

There were 360 participants randomized into the original MAPIT study. From the 360 individuals who completed the baseline interview, 21 individuals were lost to follow-up and removed from the current study's dataset (Table 1).

Table 1: Individual cases lost to follow-up			
B00159	B00920	B01308	D10613
B00586	B00997	B01409	D10653
B00692	B01032	D10080	D10664
B00696	B01055	D10144	D10838
B00904	B01128	D10612	D10859
D10885			

From the 339 individuals who completed some type of follow-up, 11 individuals were lost to the six-month follow-up and removed from the current study's dataset (Table 2).

Table 2: Individual cases lost to 6 month follow-up			
B00102	B00853	D10114	D10496
B00326	B00948	D10238	D10558
B00757	B00958	D10325	

From the 328 individuals who completed the six-month follow-up, one case (B00459) was removed for missing 143 days of follow-up (79%) due to the interviewer skipping the days during the interview. From the remaining 327 individuals, seven individuals were removed for missing 30 or more days of data during follow-up and removed from the current study's dataset (Table 3).

Table 3: Individual cases missing 30 days or more of follow-up data		
	Number of days missing	**Reason missing**
B00387	62.00	Interviewer skipped days
B00342	61.00	Interviewer skipped days
B00400	61.00	Interviewer skipped days
B01212	60.00	Interviewer skipped days
B00818	59.00	Interviewer skipped days
B00253	30.00	Interviewer skipped days
B01387	39.00	Interview occurred early (last day is day 141)

Cross-examining the remaining 320 individuals with the arrest outcome revealed that 15 cases were missing arrest data. These 15 cases were removed from the current study's dataset (Table 4).

Table 4: Individual cases missing arrest outcome				
B00731	B01156	B01395	D10209	D10291
B00871	B01270	B01434	D10260	D10333
B00962	B01329	D10198	D10282	D10668

The remaining 305 individuals did have some missing data to address. Among these cases, 31 cases[4] had one or two days missing (Table 5). Most of this missing data was due to the interviewing skipping days during the TLFB day-to-day examination of substance use. Ten of these were because the interview happened a day or two before the 180 day follow-up time. For these cases, the 14 days before and after the missing data point were examined to check the pattern of use. Largely, there was no pattern, minimal use, or no use in the time period around the missing data. Due to this, the decision was made to be conservative in replacing the missing data and assuming no use on those missing data points.

Further among the remaining 305 individuals, one case[5] had 17 days missing (i.e., B00650) due to the interviewer skipping days. With this case, the 30 days before and after the missing data point were examined to check the pattern of use. The case only had one day of opiate and cocaine use. Given there was minimal use in the time period around the missing days, the missing data points were assumed to be no use.

[4] 3 cases (D10198, D10209, B01434) fell under this criteria, but had been removed due to missing arrest data.

[5] Another case (D10333) had 10 days missing, but had already been removed due to missing arrest data.

Table 5: Individual cases missing 1-2 days of substance use days data		
	Number of days missing	**Reason missing**
D10841	2.00	Interviewer skipped days
B00556	1.00	Interviewer skipped days
B00056	1.00	Interviewer skipped days
B00119	1.00	Interviewer skipped days
B00178	1.00	Interviewer skipped days
B00303	1.00	Interviewer skipped days
B00321	1.00	Interviewer skipped days
B00374	1.00	Interviewer skipped days
B00522	1.00	Interviewer skipped days
B01335	1.00	Interviewer skipped days
D10034	1.00	Interviewer skipped days
D10047	1.00	Interviewer skipped days
D10215	1.00	Interviewer skipped days
D10244	1.00	Interviewer skipped days
D10296	1.00	Interviewer skipped days
D10297	1.00	Interviewer skipped days
D10452	1.00	Interviewer skipped days
D10461	1.00	Interviewer skipped days
D10617	1.00	Interviewer skipped days
D10733	1.00	Interviewer skipped days
D10798	1.00	Interviewer skipped days
D10086	1.00	Interviewer skipped days
B00767	2.00	Interview occurred early (last day is day 178)
B01086	2.00	Interview occurred early (last day is day 178)
B01203	2.00	Interview occurred early (last day is day 178)
D10007	2.00	Interview occurred early (last day is day 178)
D10172	2.00	Interview occurred early (last day is day 178)
B00340	1.00	Interview occurred early (last day is day 179)
B00560	1.00	Interview occurred early (last day is day 179)
B00695	1.00	Interview occurred early (last day is day 179)
B01318	1.00	Interview occurred early (last day is day 179)

Another seven cases[6] had missing data at the end of the follow-up period due to the interview occurring earlier than the six-month follow-up resulting in more than two

[6] There were originally nine cases, but one of them had already been removed based on having more than 30 days of missing data because the interviewer skipped days (B00818), and one case (B01329) had been removed for not having arrest data.

days of missing data (Table 6). Due to the longer period of missing data, the approach taken to replace these data points was to impute this data with the corresponding days in month five of the follow-up. The inclusion of these eight imputed cases were examined in sensitivity analysis below before deciding how to handle them in the current study's analyses.

Table 6: Individual cases missing data due to an early interview (more than two days missing)

	Days missing	Replacement days
B00847	19.00 (162-180)	132-150
B00967	11.00 (170-180)	140-150
B00389	9.00 (172-180)	142-150
B00538	8.00 (173-180)	143-150
B01396	6.00 (175-180)	145-150
B01219	5.00 (176-180)	146-450
B01045	4.00 (177-180)	147-150

Consideration of Other Influential Cases

An additional 22 cases[7] were found to violate the substance use eligibility criteria (Table 7). For the original MAPIT study, to be eligible for the study, participants had to report at least one day of binge alcohol use (>=five drinks per day for men; >=four drinks per day for women) or one day of any illicit drug use in the 90 days before the interview. Given that the substance use reported for screening contradicted information provided on

[7] One client was removed from the major findings paper (Lerch et al., 2017) for insufficient substance use not listed here because that case had already been removed for not having 6-month follow-up data (B00853). Three additional clients fell under this violation, but were already removed for missing arrest data (B01156; D10282; B00871).

the baseline interview, these individual cases were examined further below for any influence they have on the trajectories presented in the current study.

Table 7: Individual cases violating substance use eligibility criteria	
	Responses to substance questions at screening
B00207	Monthly binge alcohol use
B00306	Daily or almost daily binge alcohol use & 1 day illicit drug use
B00374	1 day illicit drug use
B00443	1 day illicit drug use
B00606	Daily or almost daily binge alcohol use
B00695	Weekly binge alcohol use
B00820	15 days illicit drug use
B00949	Monthly binge alcohol use
B01318	Monthly binge alcohol use & 3 days illicit drug use
B01328	Less than monthly binge alcohol use
D10009	Monthly binge alcohol use
D10097	1 day illicit drug use
D10185	No binge alcohol use or illicit drug use
D10188	Daily or almost daily binge alcohol use & 90 days illicit drug use
D10253	No binge alcohol use or illicit drug use
D10394	No binge alcohol use or illicit drug use
D10417	Weekly binge alcohol use & 36 days illicit drug use
D10617	Weekly binge alcohol use & 12 days illicit drug use
D10621	Weekly binge alcohol use
D10626	1 day illicit drug use
D10777	Less than monthly binge alcohol use & 8 days illicit drug use
D10839	Monthly binge alcohol use

Sample Size Selection

Several alternative samples were examined to determine the potential influence that the handling of missing data and removal of cases that violated the original studies substance use criteria had on the trajectory results and determine the most appropriate sample for the current study's final analysis. For each of the following samples, the model fit statistics (i.e., BIC and OCC) and trajectory results were examined to identify any significant differences across eight potential trajectory groups.

- Sample A (N=320): This sample includes the 15 cases removed due to the arrest outcome data missing.
- Sample B (N=305): This sample removes the 15 cases missing arrest outcome data.
- Sample C (N=297): This sample removes the 15 cases missing arrest outcome data *and* the eight cases where more than two days of missing substance use data were imputed.
- Sample D (N=283): This sample removes the 15 cases missing arrest outcome data *and* the 22 cases that violated the substance use eligibility criteria for the original study.
- Sample E (N=275): This sample removes the 15 cases missing arrest outcome data, the eight cases where more than two days of missing substance use data were imputed, *and* the 22 cases that violated the substance use eligibility criteria for the original study.

Sample A (N=320)

For sample A, the BIC is less negative for each model, indicating that every model is a better fit than the previous model (Table 8). Table 9 presents the population size distribution across groups and the odds of correct classification (OCC) for the models with five-, six-, and seven-groups. The average posterior probability for these groups all exceeded 0.7.

Table 8: Sample A Model Fit Statistics (N=320)				
Number of Groups	**Order**	**Iorder**	**BIC (N=1920)[1]**	**BIC (N=320)[2]**
2	22	2	-4855.64	-4846.69
3	222	2	-4327.99	-4315.45
4	2222	2	-4109.70	-4093.57
5	22222	2	-4008.63	-3988.92
6	222222	2	-3847.04	-3823.75
7	2222222	2	-3820.94	-3794.06
8	22222222	2	-3798.20	-3767.74
BIC[1]=overall sample size; BIC[2]=subject sample size				

Table 9: Sample A Trajectory Percentage Distribution and OCC Comparison (N=320)						
	5-Group		**6-Group**		**7-Group**	
	Percent	**OCC**	**Percent**	**OCC**	**Percent**	**OCC**
1	48.6	53.91373819	45.1	57.45227154	34.2	18.83235612
2	14.0	104.4585205	12.6	48.706121	15.8	35.88904767
3	10.8	74.36617455	12.1	109.0908875	11.7	81.65910748
4	7.8	145.6158833	8.5	300.5536998	9.7	165.2796327
5	18.7	190.1108869	8.7	147.2698671	8.4	263.1803518
6			13.1	81.2972862	7.6	151.1091507
7					12.5	69.57812451

The five-, six-, and seven-group models are depicted in Figures 1 through 3. Comparing these three models, the six-group model (Figure 2) provides an additional interpretable trajectory not present in the five-group model (Figure 1). However, the seven-group model (Figure 3) does not provide any additional interpretability beyond that of the six-group model. Trajectories one and two in the seven-group model appear identical, whereas in the six-group model, each of these trajectories explains a different pattern of use. Due to this, the six-group model is the best fit model for this sample.

Figure 1: Sample A Five Group Expected (dashed) vs. Observed (solid) Trajectories

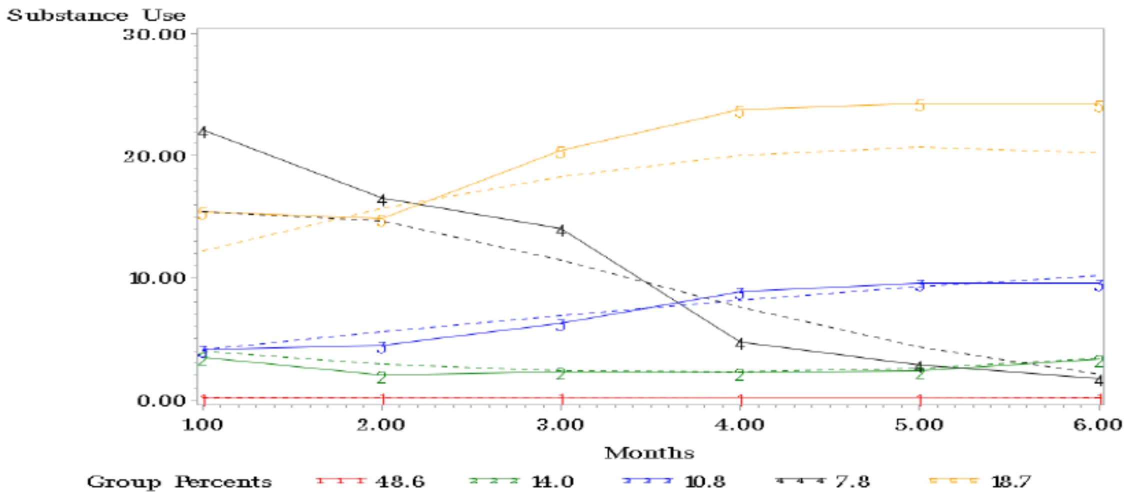


Figure 2: Sample A Six Group Expected (dashed) vs. Observed (solid) Trajectories

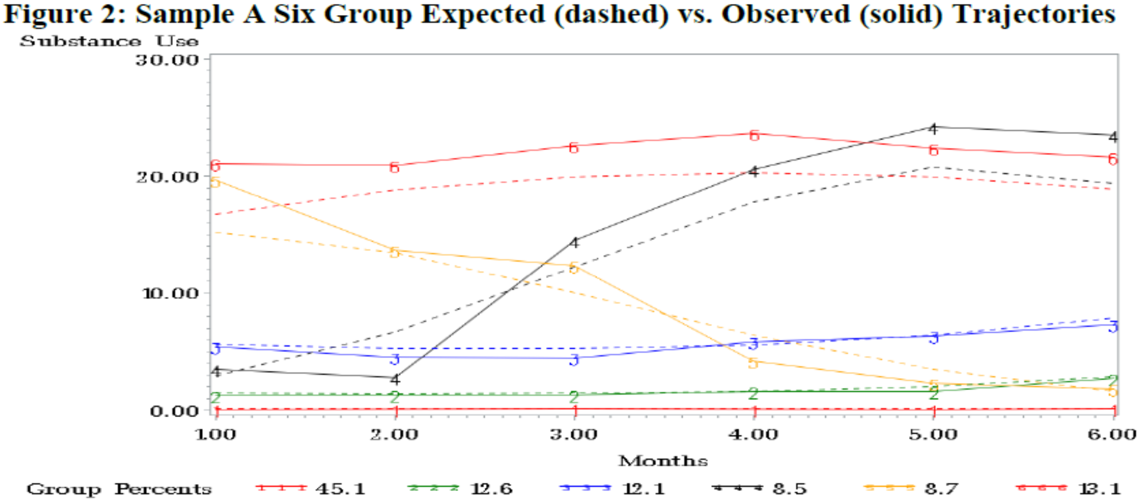
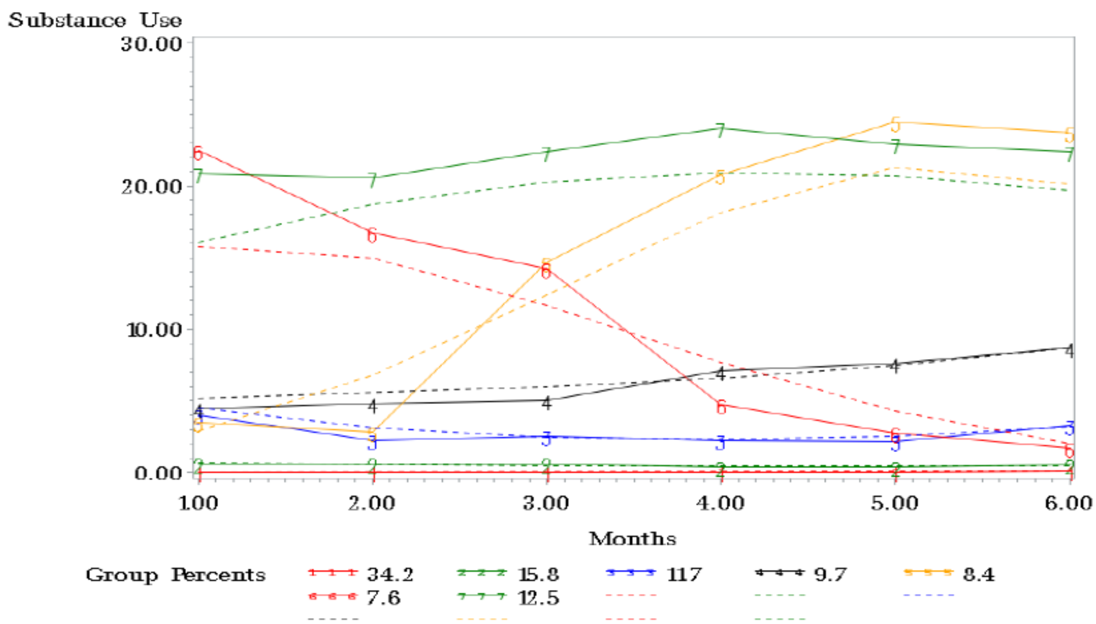


Figure 3: Sample A Seven Group Expected (dashed) vs. Observed (solid) Trajectories



Sample B (N=305)

For sample B, the BIC is less negative for each model, indicating that every model is a better fit than the previous model (Table 10). Table 11 presents the population size distribution across groups and the OCC for the models with five-, six-, and seven-groups. The average posterior probability for these groups all exceeded 0.7.

Table 10: Sample A Model Fit Statistics (N=305)				
Number of Groups	**Order**	**Iorder**	**BIC (N=1830)[1]**	**BIC (N=305)[2]**
2	22	2	-4723.90	-4714.94
3	222	2	-4209.25	-4196.71
4	2222	2	-3995.77	-3979.64
5	22222	2	-3903.51	-3883.80
6	222222	2	-3751.58	-3728.29
7	2222222	2	-3728.39	-3701.52
8	22222222	2	-3695.26	-3664.80
BIC[1]=overall sample size; BIC[2]=subject sample size				

Table 11: Sample B Trajectory Percentage Distribution and OCC Comparison (N=305)						
	5-Group		**6-Group**		**7-Group**	
	Percent	**OCC**	**Percent**	**OCC**	**Percent**	**OCC**
1	47.5	57.85816161	44.7	67.5373542	24.5	24.58966997
2	13.9	112.6776069	12.7	48.01184931	24.2	93.42015697
3	11.1	90.92467857	13.6	75.41522597	12.3	87.21268341
4	8.0	171.1018118	8.9	137.9001049	10.0	147.0469271
5	19.6	124.8414208	7.2	266.8941035	8.2	147.5881528
6			12.9	77.74379193	7.8	191.3390913
7					13.0	73.46547853

The five-, six-, and seven-group models are depicted in Figures 4 through 6. Just as with the sample A, the six-group model (Figure 5) provides an additional interpretable trajectory not present in the five-group model (Figure 4). However, the seven-group model (Figure 6) does not provide any additional interpretability beyond that of the six-group model. Trajectories one and two in the seven-group model appear identical, whereas in the six-group model, each of these trajectories explains a different pattern of use. Due to this, the six-group model is the best fit model for this sample.

Figure 4: Sample B Five Group Expected (dashed) vs. Observed (solid) Trajectories

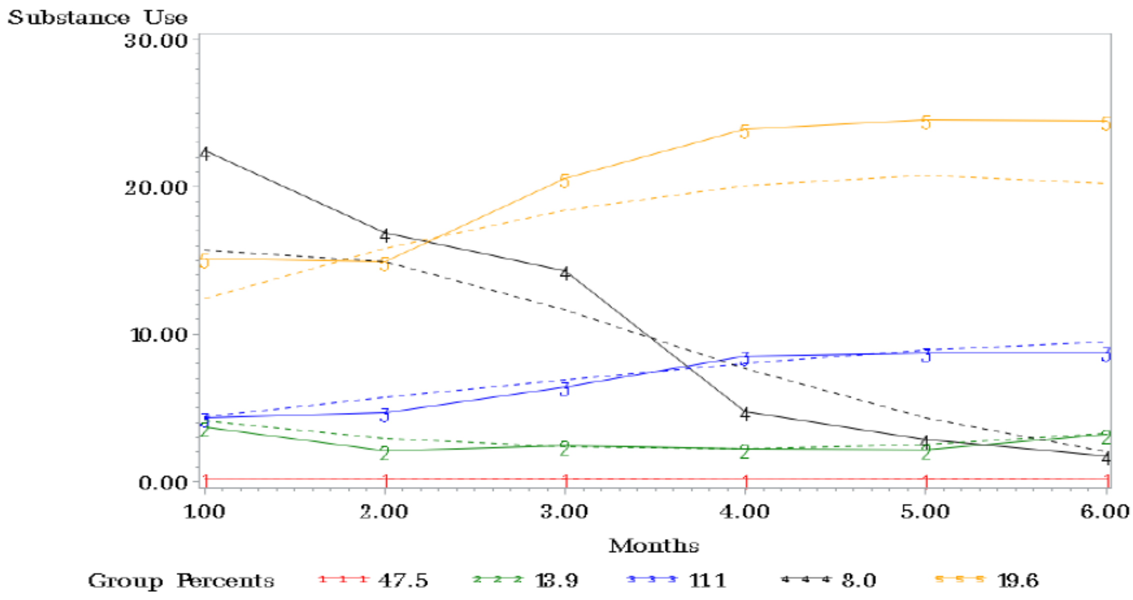


Figure 5: Sample B Six Group Expected (dashed) vs. Observed (solid) Trajectories

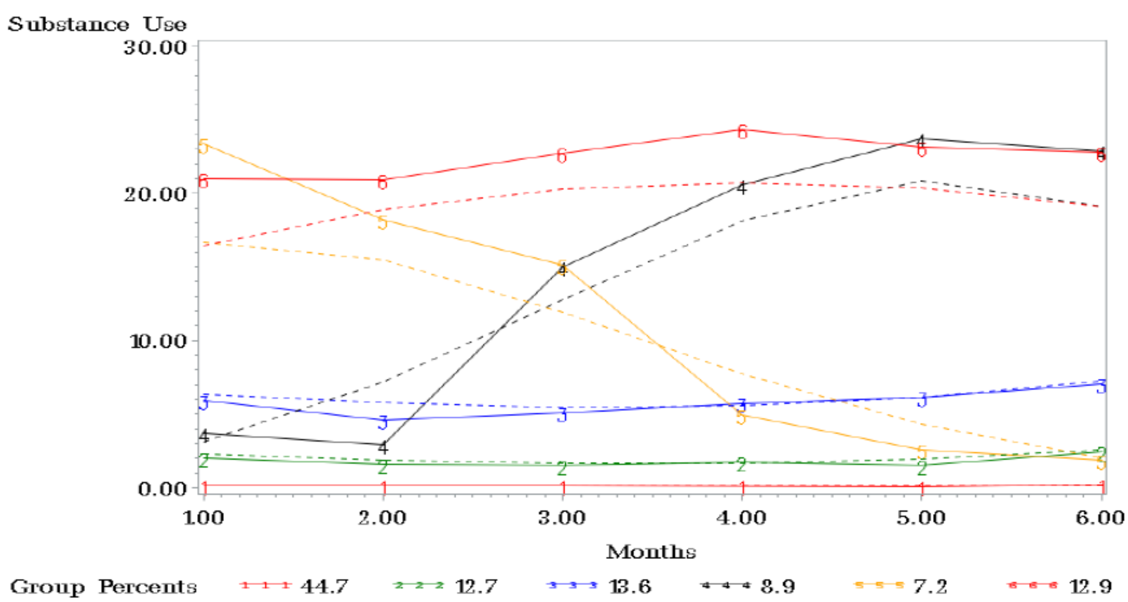
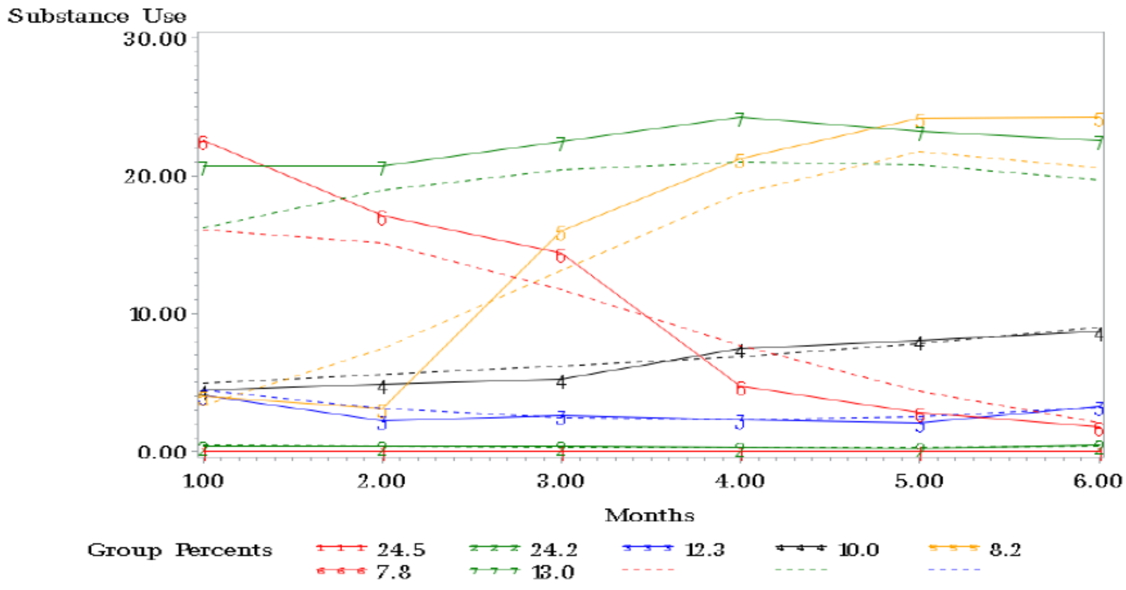


Figure 6: Sample B Seven Group Expected (dashed) vs. Observed (solid) Trajectories



Sample C (N=297)

For sample C, the BIC is less negative for each model, indicating that every model is a better fit than the previous model (Table 12). Table 13 presents the population size distribution across groups and the OCC for the models with five-, six-, and seven-groups. The average posterior probability for these groups all exceeded 0.7.

Table 12: Sample C Model Fit Statistics (N=297)				
Number of Groups	**Order**	**Iorder**	**BIC (N=1782)[1]**	**BIC (N=297)[2]**
2	22	2	-4562.41	-4553.46
3	222	2	-4059.94	-4047.40
4	2222	2	-3857.00	-3840.88
5	22222	2	-3767.39	-3747.68
6	222222	2	-3660.66	-3637.36
7*	2222222	2	-3599.26	-3572.39
8	22222222	2	-3552.34	-3521.88

BIC[1]=overall sample size; BIC[2]=subject sample size
*Unable to calculate standard errors.

Table 13: Sample C Trajectory Percentage Distribution and OCC Comparison (N=297)						
	5-Group		**6-Group**		**7-Group**	
	Percent	**OCC**	**Percent**	**OCC**	**Percent**	**OCC**
1	47.9	54.92482465	25.3	25.20630315	24.6	20.64043534
2	14.0	180.0965836	24.1	158.8428901	24.1	167.9316119
3	11.5	76.68388543	17.3	64.9135848	12.6	82.83049132
4	7.1	167.3267557	8.9	202.1972171	10.4	114.1292241
5	19.4	120.4670901	10.2	118.5046192	8.2	176.314875
6			14.2	72.31917628	7.0	226.5463959
7					13.0	73.54835949

The five-, six-, and seven-group models are depicted in Figures 7 through 9. Comparing these models, the five-group model (Figure 7) is interpretable and clinically relevant. The six- (Figure 8) and seven- (Figure 9) group models do not provide any additional interpretability beyond that of the five-group model. In these models, trajectories one and two are not interpretably distinct. Due to this, the five-group model is the best fit model for this sample.

Figure 7: Sample C Five Group Expected (dashed) vs. Observed (solid) Trajectories

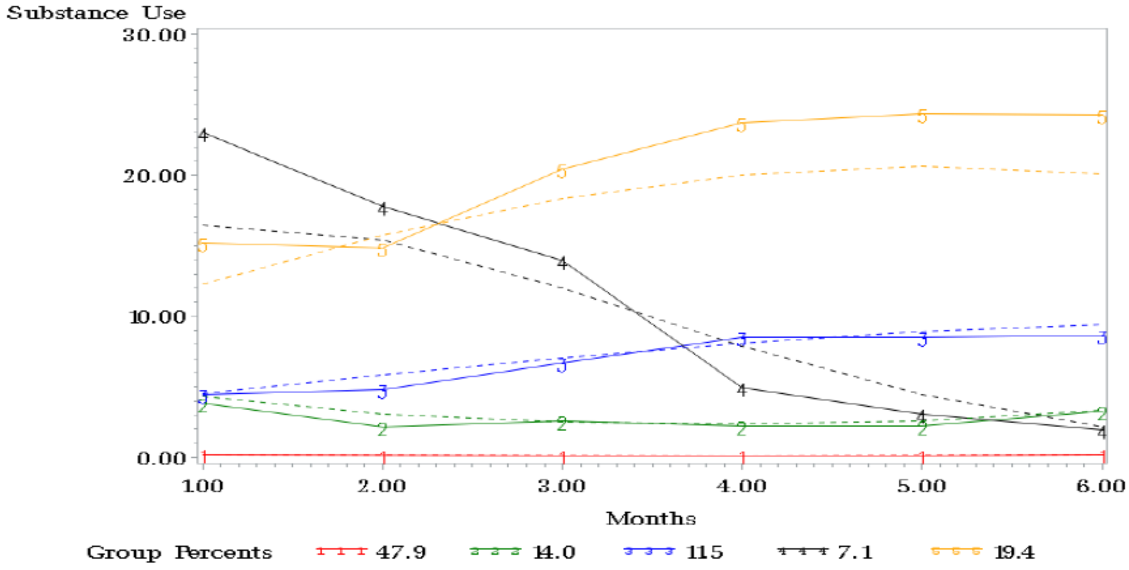


Figure 8: Sample C Six Group Expected (dashed) vs. Observed (solid) Trajectories

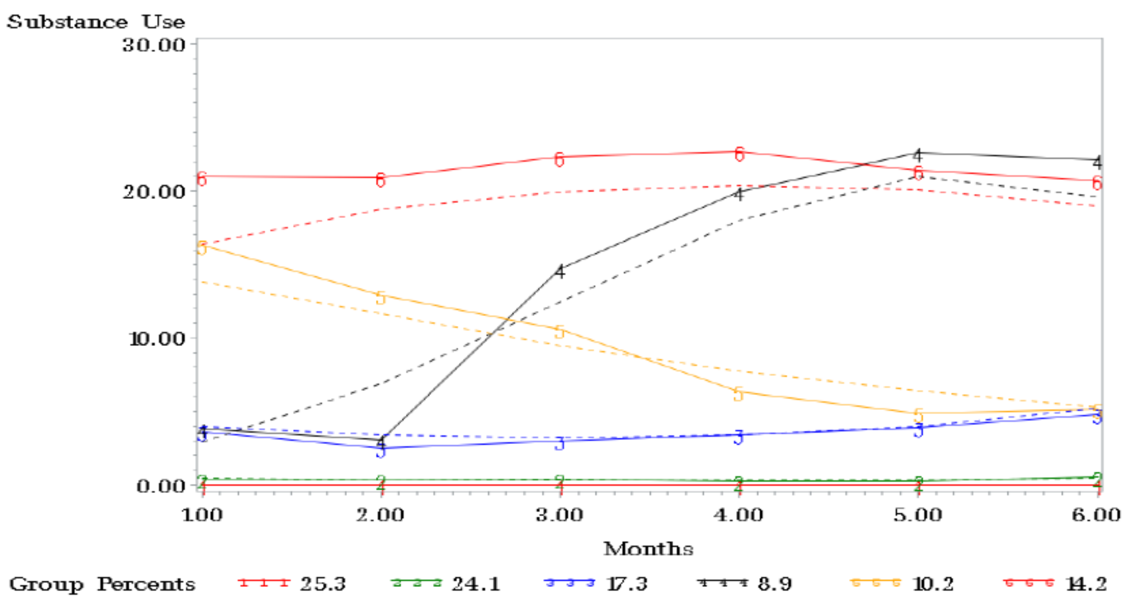
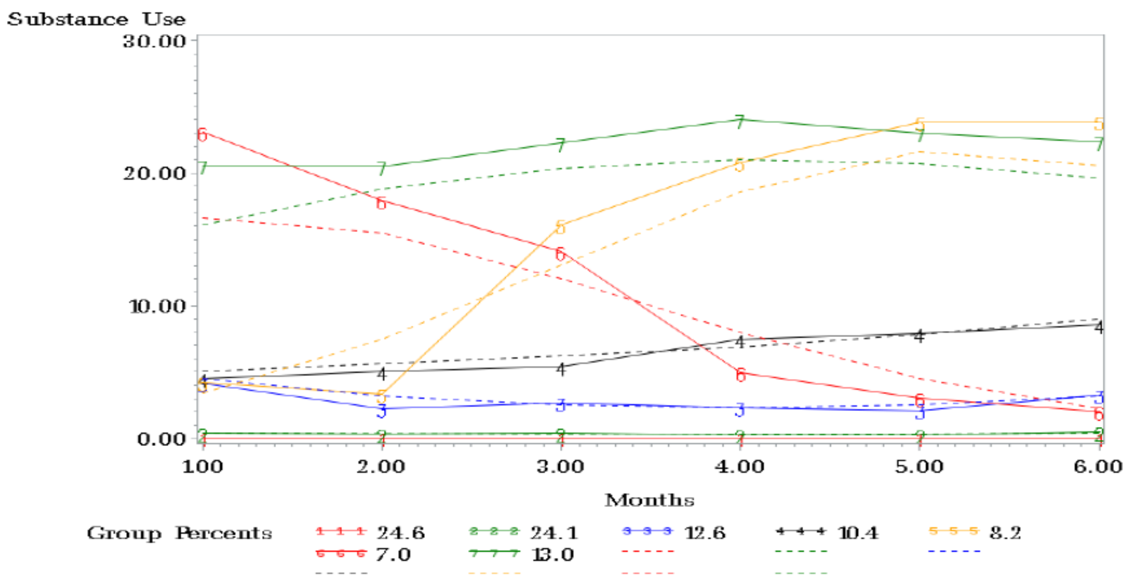


Figure 9: Sample C Seven Group Expected (dashed) vs. Observed (solid) Trajectories



Sample D (N=283)

For sample D, the BIC is less negative for each model through the seven-group model. Then, for the eight-group model, the BIC increases in value, suggesting that the seven-group model is the better, more parsimonious model (Table 14). Table 15 presents the population size distribution across groups and the OCC for the models with five-, six-, and seven-groups. The average posterior probability for these groups all exceeded 0.7.

Table 14: Sample D Model Fit Statistics (N=283)				
Number of Groups	**Order**	**Iorder**	**BIC (N=1698)[1]**	**BIC (N=283)[2]**
2	22	2	-4572.76	-4563.81
3	222	2	-4082.67	-4070.13
4	2222	2	-3878.63	-3862.51
5	22222	2	-3782.22	-3762.52
6	222222	2	-3622.78	-3599.49
7	2222222	2	-3588.94	-3562.07
8	22222222	2	-3624.32	-3593.86
BIC[1]=overall sample size; BIC[2]=subject sample size				

Table 15: Sample D Trajectory Percentage Distribution and OCC Comparison (N=283)						
	5-Group		**6-Group**		**7-Group**	
	Percent	**OCC**	**Percent**	**OCC**	**Percent**	**OCC**
1	45.5	62.32582818	45.4	58.50781043	42.3	37.99170732
2	13.2	126.8985952	12.8	143.5687019	12.4	61.76472923
3	12.2	95.96555557	11.0	111.2201894	6.9	275.5911777
4	8.7	124.918425	8.7	209.471722	11.1	118.0898376
5	20.5	127.0561736	8.5	129.5746586	9.4	121.6645228
6			13.5	81.68043902	5.0	1269.081139
7					12.9	77.45794939

The five-, six-, and seven-group models are depicted in Figures 10 through 12. Comparing these models, all three models present interpretable and clinically relevant trajectory groups. Of these models, the seven-group (Figure 12) model appears to contribute an additional, interpretable trajectory that the five- (Figure 10) and six- (Figure 11) group models do not. Due to this, the seven-group model is the best fit model for this sample.

Figure 10: Sample D Five Group Expected (dashed) vs. Observed (solid) Trajectories

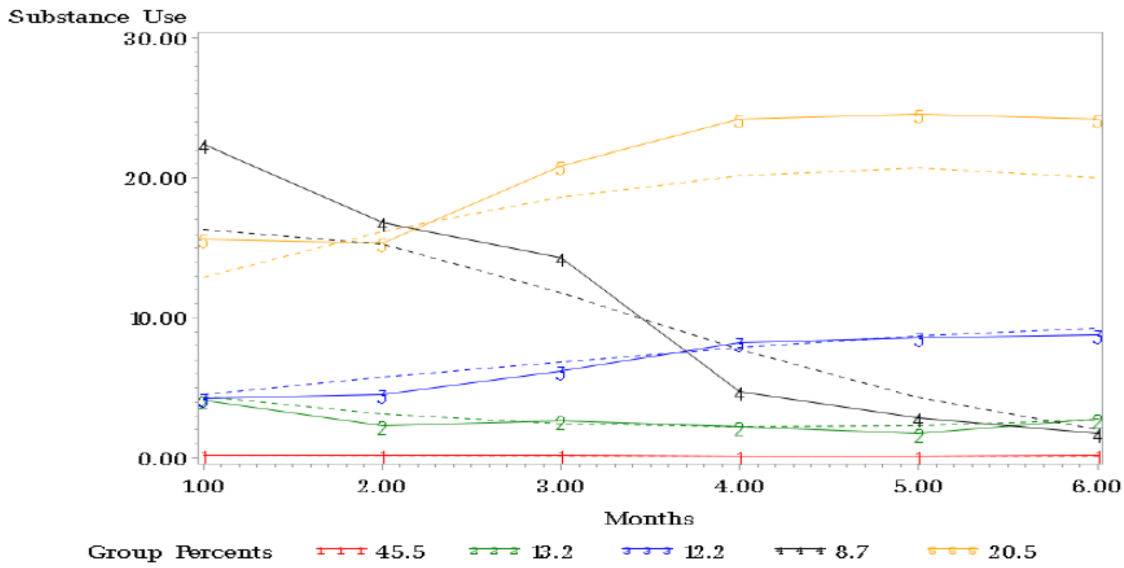


Figure 11: Sample D Six Group Expected (dashed) vs. Observed (solid) Trajectories

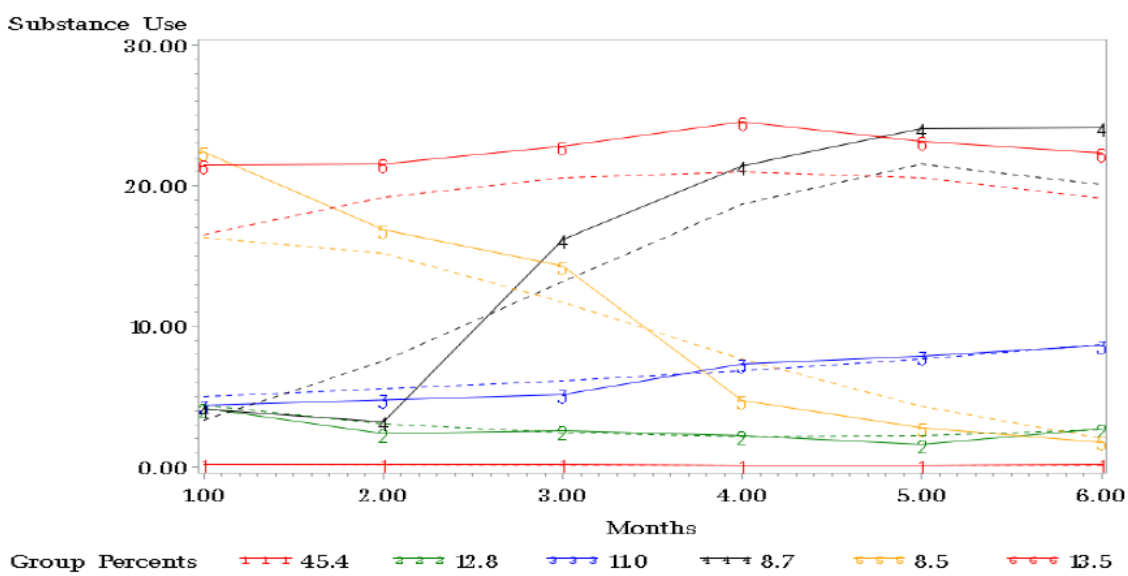
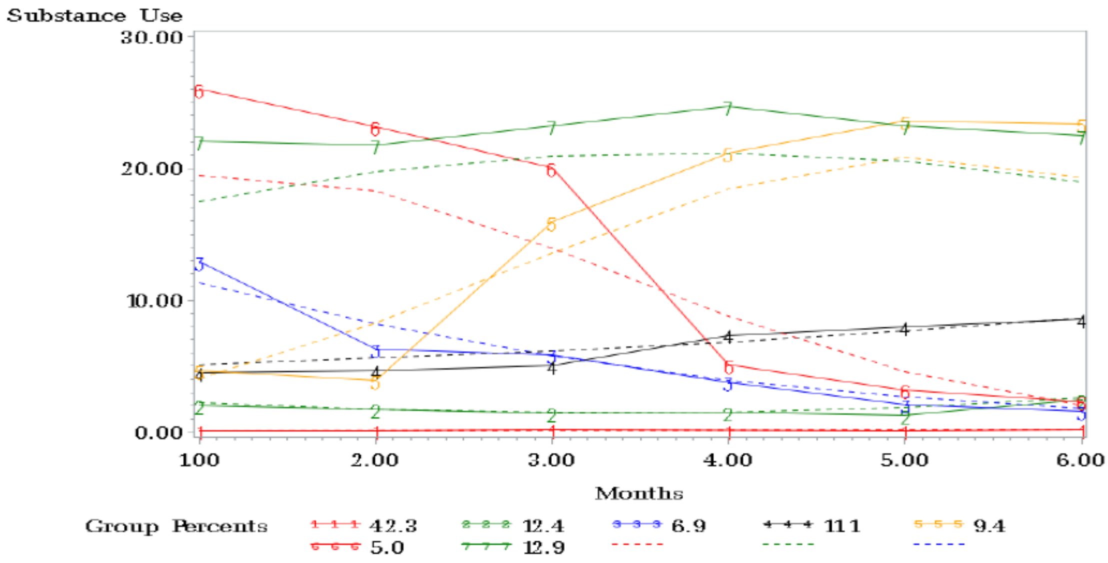


Figure 12: Sample D Seven Group Expected (dashed) vs. Observed (solid) Trajectories



Sample E (N=275)

For sample E, the BIC is less negative for each model through the seven-group model. Then, for the eight-group model, the BIC increases in value. However, the difference between the six- and seven-group models is negligible, with the overall sample size BIC for the seven-group model being less than 10 from the six-group and just a little over 10 difference for the subject sample size BIC (Table 16). Table 17 presents the population size distribution across groups and the OCC for the models with five-, six-, and seven-groups. The average posterior probability for these groups all exceeded 0.7.

Table 16: Sample E Model Fit Statistics (N=275)				
Number of Groups	**Order**	**Iorder**	**BIC (N=1650)[1]**	**BIC (N=275)[2]**
2	22	2	-4411.52	-4402.56
3	222	2	-3938.08	-3925.54
4	2222	2	-3740.90	-3724.77
5	22222	2	-3647.31	-3627.60
6	222222	2	-3490.98	-3467.68
7	2222222	2	-3481.91	-3455.03
8	22222222	2	-3491.51	-3461.05
BIC[1]=overall sample size; BIC[2]=subject sample size				

Table 17: Sample E Trajectory Percentage Distribution and OCC Comparison (N=275)						
	5-Group		**6-Group**		**7-Group**	
	Percent	**OCC**	**Percent**	**OCC**	**Percent**	**OCC**
1	45.9	75.09973705	45.8	70.28583803	22.2	21.60464351
2	13.2	90.77296812	12.8	127.9594077	24.3	182.0046637
3	12.8	102.4740143	11.5	110.9943346	12.3	96.9285712
4	7.8	168.1941922	8.7	170.7284997	11.4	110.6720245
5	20.3	129.0561493	7.7	218.4476496	8.7	170.9851593
6			13.5	81.94999946	7.6	218.4777966
7					13.5	81.85279613

The five-, six-, and seven-group models are depicted in Figures 13 through 15. Comparing these models, the five- (Figure 13) and six- (Figure 14) group models present interpretable and clinically relevant trajectory groups. Of these models, the seven-group (Figure 15) model does not appear to contribute any additional, interpretable trajectory from that of the five- or six-group models. Due to this, the six-group model is the best fit model for this sample.

Figure 13: Sample E Five Group Expected (dashed) vs. Observed (solid) Trajectories

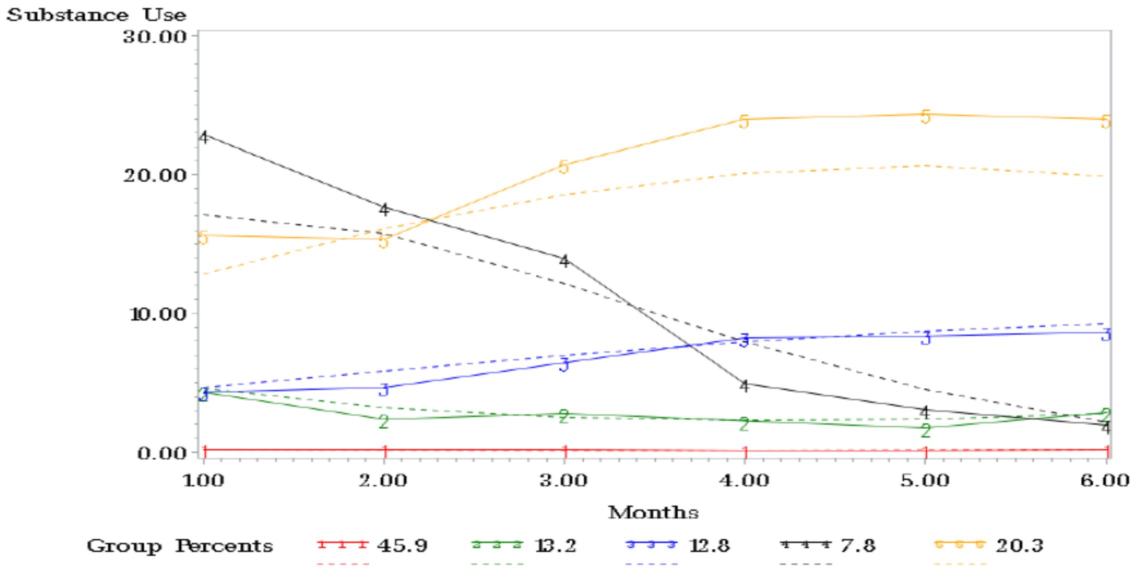


Figure 14: Sample E Six Group Expected (dashed) vs. Observed (solid) Trajectories

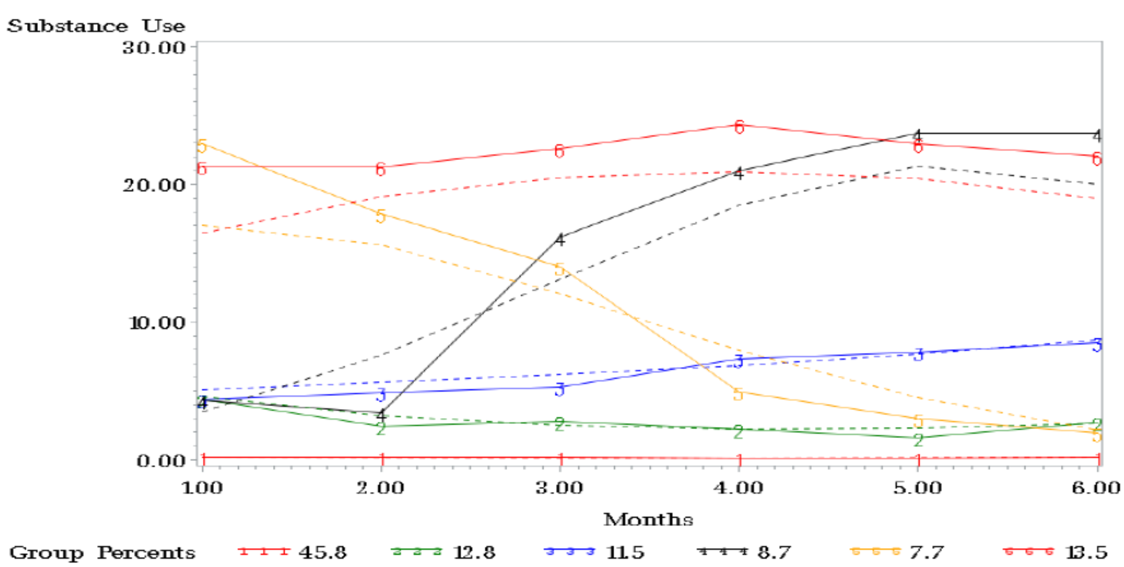
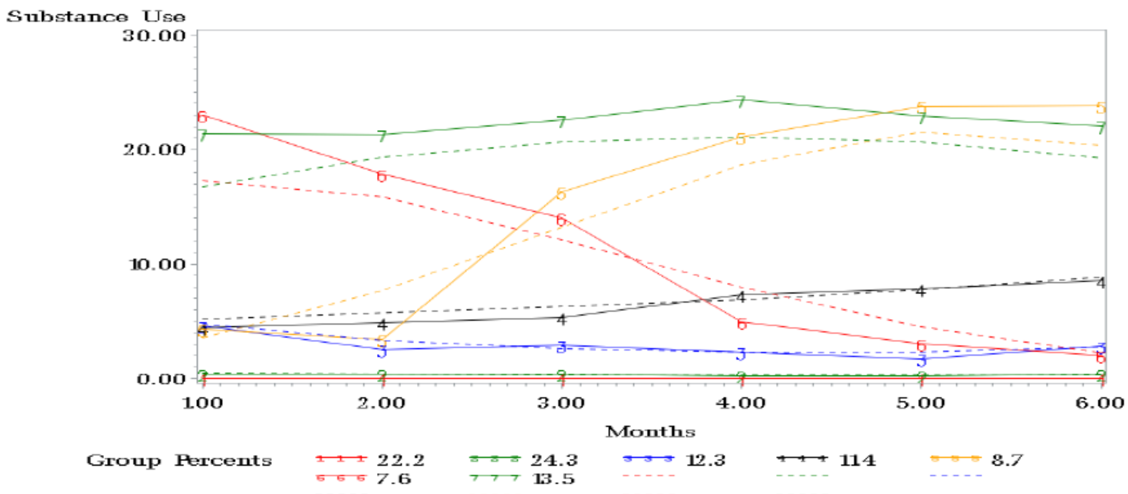


Figure 15: Sample E Seven Group Expected (dashed) vs. Observed (solid) Trajectories



Final Sample Selection

Examining the above models revealed that the cases with missing data replaced for more than two days and that violated the substance use criteria for the original study do have an influence on the group-based trajectory models. Given the potential for incorrect data in these cases, the decision was made to remove them from the final sample used in the current study. The cases that violated the substance use criteria for the original MAPIT study demonstrated inconsistencies that may reflect inaccurate data during the baseline interview. The cases with missing data replaced for more than two days missing could have potentially not followed the same pattern from month-to-month, invalidating the replacement method. To be more confident in the results, these two sets of cases were removed. The final dataset for the current study includes 275 participants (Table 18).

Table 18: Sample Comparisons			
	BIC	**OCC**	**Best model selected**
Sample A (n=320)	Inconclusive	Acceptable	6-group
Sample B (n=305)	Inconclusive	Acceptable	6-group
Sample C (n=297)	Inconclusive	Acceptable	5-group
Sample D (n=283)	7-group	Acceptable	7-group
Sample E (n=275)	6- or 7-group	Acceptable	6-group

APPENDIX C: RECOGNITION SCALE DEVELOPMENT

Prior analyses with this data revealed that when the CJ-CEST subscales of problem recognition and desire for help (subscales measuring treatment motivation) were entered into a regression analysis the variance inflation factor was above the recommended threshold, indicating a problem with multi-collinearity. Following this finding, further examination revealed that these subscales were significantly correlated ($r = 0.86$, $p < 0.001$). A correlation table was examined to see how individual items within these two scales interacted. As can be seen in Table 1, all of the individual items, with the exception of Q72 ("You want to get your life straightened out."), were significantly correlated with all other items. With the exception of Q72 and Q19 ("You will give up your friends and hangouts to solve your drug problems."), the individual items had Pearson correlation values above 0.3. Based on this information, factor analysis was completed using SPSS.

The goal of the factor analysis was to identify the underlying constructs for the individual items within the problem recognition and desire for help CJ-CEST subscales. The goal was to combine potentially correlated individual variables into fewer, uncorrelated variables (constructs) (Richardson, 2009; Williams et al., 2010). The extraction method used was Principal Components Analysis (PCA) and a varimax rotation, an orthogonal rotation used to simplify interpretation by creating uncorrelated factors (Abdi & Williams, 2010; Williams et al., 2010). Five criteria were considered in determining the best solution: 1) Kaiser-Meyer-Olkin (KMO) test; 2) Bartlett's Test of Sphericity; 3) communalities extracted; 4) variance explained by the factors; and 5) factor loadings.

Table 1: Individual Item Correlations

		Q1	Q9	Q16	Q21	Q35	Q40	Q49	Q69	Q79	Q2	Q15	Q19	Q36	Q50	Q72
Q1	Pearson	1	.669**	.577**	.567**	.674**	.517**	.534**	.632**	.564**	.835**	.660**	.304**	.483**	.621**	.161**
Q9	Pearson	.669**	1	.563**	.450**	.567**	.419**	.449**	.614**	.532**	.640**	.580**	.377**	.399**	.609**	.184**
Q16	Pearson	.577**	.563**	1	.566**	.636**	.468**	.461**	.598**	.475**	.617**	.611**	.299**	.399**	.516**	.059
Q21	Pearson	.567**	.450**	.566**	1	.627**	.496**	.551**	.610**	.588**	.574**	.563**	.257**	.454**	.545**	.094
Q35	Pearson	.674**	.567**	.636**	.627**	1	.539**	.526**	.726**	.627**	.687**	.633**	.261**	.532**	.599**	.071
Q40	Pearson	.517**	.419**	.468**	.496**	.539**	1	.444**	.571**	.501**	.518**	.497**	.248**	.536**	.459**	.081
Q49	Pearson	.534**	.449**	.461**	.551**	.526**	.444**	1	.532**	.554**	.562**	.461**	.241**	.334**	.530**	.110*
Q69	Pearson	.632**	.614**	.598**	.610**	.726**	.571**	.532**	1	.691**	.648**	.613**	.282**	.565**	.628**	.123*
Q79	Pearson	.564**	.532**	.475**	.588**	.627**	.501**	.554**	.691**	1	.615**	.536**	.270**	.399**	.589**	.083
Q2	Pearson	.835**	.640**	.617**	.574**	.687**	.518**	.562**	.648**	.615**	1	.727**	.284**	.470**	.641**	.113*
Q15	Pearson	.660**	.580**	.611**	.563**	.633**	.497**	.461**	.613**	.536**	.727**	1	.289**	.485**	.561**	.073
Q19	Pearson	.304**	.377**	.299**	.257**	.261**	.248**	.241**	.282**	.270**	.284**	.289**	1	.234**	.359**	.172**
Q36	Pearson	.483**	.399**	.399**	.454**	.532**	.536**	.334**	.565**	.399**	.470**	.485**	.234**	1	.419**	.159**
Q50	Pearson	.621**	.609**	.516**	.545**	.599**	.459**	.530**	.628**	.589**	.641**	.561**	.359**	.419**	1	.212**
Q72	Pearson	.161**	.184**	.059	.094	.071	.081	.110*	.123*	.083	.113*	.073	.172**	.159**	.212**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The KMO is 0.950, demonstrating excellent sampling adequacy (Williams et al., 2010). Bartlett's Test of Sphericity is significant ($p < .001$), rejecting that the correlation matrix is an identity matrix (Williams et al., 2010). Examining the communalities, four items were found to not meet the necessary threshold of 0.5 (Williams et al., 2010). These items were the following: Q40 ("Your drug use is causing problems in finding or keeping a job."); Q49 ("Your drug use is causing problems with your health."); Q19 ("You will give up your friends and hangouts to solve your drug problems."); and Q36 ("Your life has gone out of control."). Initial Eigenvalues demonstrated that the first factor explained 53% of the variance, while a second factor explained 7% of the variance. No other factors were above the threshold of one (Williams et al., 2010). Finally, the primary factor loadings and cross-loadings in a varimax rotated matrix were examined for the primary loading to be 0.7 or above and any cross-loadings to be below 0.3. These results revealed that seven items violated the criteria (Table 2):

- Q9: "Your drug use is more trouble than it's worth."
- Q40: "Your drug use is causing problems in finding or keeping a job."
- Q49 "Your drug use is causing problems with your health."
- Q19: "You will give up your friends and hangouts to solve your drug problems."
- Q36: "Your life has gone out of control."
- Q50: "You are tired of the problems caused by drugs."
- Q72: "You want to get your life straightened out."

The final scale, called recognition, emerged from eight items that loaded as one factor, explaining 67% of the variance according to the Initial Eigenvalues. Table 3 shows the factor loadings for the final scale. The KMO is 0.920, the Bartlett's Test of Sphericity is significant, the communalities are all above 0.5, and all the primary loadings are above 0.7. The Cronbach's alpha for the final scale is 0.930.

The primary loading appears to be a measure of recognition that substance use is causing problems within the individuals' life, but potentially the individual is still functioning at an acceptable level. The items in the second loading seem to measure more of an actual desire to change behavior due to the individuals' life actually going off track. This second loading only contains one item and therefore not included in further analysis. Future research may examine these scales, including the follow-up measures of these items to see if these subscales behave similarly at different time points.

Table 2: Rotated Component Matrix[a]

	Components	
	Recognition Scale	Desire to Change
Your drug use is a problem for you.	**.804**	.241
Your drug use is more trouble than it's worth.	.687	.368
Your drug use is causing problems with the law.	**.748**	.096
Your drug use is causing problems in thinking or doing your work.	**.761**	.070
Your drug use is causing problems with your family or friends.	**.846**	.068
Your drug use is causing problems in finding or keeping a job.	**.688**	.080
Your drug use is causing problems with your health.	.677	.126
Your drug use is making your life become worse and worse.	**.831**	.148
Your drug use is going to cause your death if you do not quit soon.	**.764**	.103
You need help in dealing with your drug use.	**.842**	.170
It is urgent that you find help immediately for your drug use.	**.790**	.117
You will give up your friends and hangouts to solve your drug problems.	.274	.594
Your life has gone out of control.	.608	.185
You are tired of the problems caused by drugs.	**.710**	.359
You want to get your life straightened out.	-.047	**.858**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table 3: Component Matrix[a]

	Recognition Scale
Your drug use is a problem for you.	**.844**
Your drug use is causing problems with the law.	.772
Your drug use is causing problems in thinking or doing your work.	.772
Your drug use is causing problems with your family or friends.	**.858**
Your drug use is making your life become worse and worse.	**.842**
Your drug use is going to cause your death if you do not quit soon.	.774
You need help in dealing with your drug use.	**.874**
It is urgent that you find help immediately for your drug use.	**.816**

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

APPENDIX D: SENSITIVITY ANALYSES

Time on Probation Outliers Sensitivity Analysis

Examining the time-stable predictor time on probation from the baseline interview reveals that four cases are outliers: D10026, D10113, D10168, and D10441. Looking at the characteristics of these individuals, it appears that case D10441 contains inconsistent probation time in comparison to the sentenced time on probation (Table 1). The other cases appear to have a reasonable amount of time on probation reported as compared to the sentenced time on probation. Table 2 presents the comparison of overall sample descriptive statistics if the outlier cases were removed completely. There are no notable changes with the exception of the statistics for the variable time on probation, as anticipated. Next, the GBTM model statistics for these differing sample sizes were compared in Table 3. Again, these statistics did not change considerably. There were some shifts among group proportions comparing the different sample sizes, but not notably. Looking at the trajectories of these two differing samples (i.e., 274 and 271), the interpretability of these trajectories do not change from the sample of 275 (Figures 1 and 2). Given these findings, the researcher decided to keep all the cases in the analysis dataset; however, the data for D10441 time on probation was changed to missing given the inconsistencies with the data. To further examine this decision, the bivariate statistics examining time-stable predictors for the groups were compared to before and after

D10441's time on probation data was changed and there were no significant changes; thus there were also no changes in the final trajectory model that incorporates the time-stable and time-varying predictors in the groups.

Table 1: Examining Characteristics across Outlier Cases

Variables	D10026 N(%) / M±SD	D10113 N(%) / M±SD	D10168 N(%) / M±SD	D10441
Demographics				
Female	Male	Male	Male	Male
Nonwhite	Nonwhite	Nonwhite	White	Nonwhite
Stable housing	Yes	Yes	Yes	No
High school diploma	No	No	No	No
Committed relationship	Yes	No	No	Yes
Unemployed	Yes	Yes	Yes	Yes
Age	39	25	46	28
Prior Substance Treatment and Use History				
Lifetime prior treatment	No	Yes	Yes	Yes
Initiated use 15 and under	Yes	Yes	Yes	Yes
Hard drug use	No	No	No	Yes
Recent IV drug user	No	No	No	No
Consequences of use	8	10	17	5
Family/peer drug use	1	1.7	1	2.3
ASI alcohol severity	0.1	0.5	0.1	0.2
ASI drug severity	0.1	0.0	0.0	0.2
Criminal Justice				
Drug testing condition	Yes	Yes	Yes	Yes
Drug treatment condition	No	Yes	No	Yes
Drug instant offense	No	No	No	No
Criminal justice static risk score	2	2	7	6
Months sentenced to probation	120	36	120	84
Days on probation	2124	768	1203	2639
Psychosocial				
Risk of mental disorders	No	No	No	No
Risk of severe mental disorders	No	Yes	Yes	No
Self-esteem	36.7	35	33.3	38.3
Decision-making	37.8	35.6	34.4	34.4
Hostility	18.8	37.5	22.5	22.5
Risk taking	17.1	27.1	31.4	25.7
Recognition	17.3	33.6	25.5	36.4
Social support	3.8	4.4	4.4	5
Self-determination	4.1	2.7	Missing	4.6
Additional controls				
MI	Yes	Yes	No	Yes
MAPIT	No	No	Yes	No
Dallas	Yes	Yes	Yes	Yes

Table 2: Comparing Sample Descriptive Statistics

Variables	Sample of 271 N(%) / M±SD	Sample of 274 N(%) / M±SD	Sample of 275 N(%) / M±SD
Demographics			
Female	85 (31.4)	85 (31.0)	85 (30.9)
Nonwhite	211 (78.1)	213 (78.0)	214 (78.1)
Stable housing	211 (77.9)	214 (78.1)	214 (77.8)
High school diploma	105 (38.7)	105 (38.3)	105 (38.2)
Committed relationship	152 (56.1)	153 (55.8)	154 (56.0)
Unemployed	143 (52.8)	146 (53.3)	147 (53.5)
Age	34.7 ± 11.6	34.8 ± 11.6	34.7 ± 11.5
Prior Substance Treatment and Use History			
Lifetime prior treatment	133 (49.1)	135 (49.3)	136 (49.5)
Initiated use 15 and under	174 (64.2)	177 (64.6)	178 (64.7)
Hard drug use	142 (52.4)	142 (51.8)	143 (52.0)
Recent IV drug user	24 (8.9)	24 (8.8)	24 (8.7)
Consequences of use	15.6 ± 12.4	15.6 ± 12.4	15.5 ± 12.4
Family/peer drug use	1.8 ± 0.8	1.8 ± 0.8	1.8 ± 0.7
ASI alcohol severity	0.2 ± 0.2	0.2 ± 0.2	0.2 ± 0.2
ASI drug severity	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Criminal Justice			
Drug testing condition	196 (72.3)	199 (72.6)	200 (72.7)
Drug treatment condition	97 (35.8)	98 (35.8)	99 (36.0)
Drug instant offense	121 (44.6)	121 (44.2)	121 (44.0)
Criminal justice static risk score	4.3 ± 2.0	4.3 ± 2.0	4.3 ± 2.0
Months sentenced to probation	31.9 ± 67.4	32.6 ± 67.4	32.8 ± 67.4
Days on probation	29.3 ± 70.3	43.9 ± 166.7	53.3 ± 228.4
Psychosocial			
Risk of mental disorders	32 (11.9)	32 (11.7)	32 (11.7)
Risk of severe mental disorders	101 (37.4)	103 (37.7)	103 (37.6)
Self-esteem	35.3 ± 8.0	35.3 ± 7.9	35.3 ± 7.9
Decision-making	37.0 ± 4.9	37.0 ± 4.9	37.0 ± 4.9
Hostility	26.8 ± 6.8	26.8 ± 6.9	26.7 ± 6.9
Risk taking	28.5 ± 6.2	28.4 ± 6.3	28.4 ± 6.2
Recognition	27.8 ± 9.3	27.8 ± 9.3	27.8 ± 9.3
Social support	3.8 ± 1.1	3.8 ± 1.1	3.8 ± 1.1
Self-determination	3.8 ± 0.8	3.8 ± 0.8	3.8 ± 0.9
Additional controls			
MI	85 (31.4)	87 (31.8)	88 (32.0)
MAPIT	93 (34.3)	94 (34.3)	94 (34.2)
Dallas	163 (60.1)	166 (60.6)	167 (60.7)

Table 3: GBTM Model Comparison using BIC and Estimated Group Proportions

Sample	BIC (overall sample size)	BIC (subject sample size)	Estimated Group Proportions					
			1	2	3	4	5	6
275	**-3478.14**	**-3458.43**	**45.7**	**12.8**	**11.5**	**8.8**	7.7	**13.5**
274	-3478.63	-3458.92	45.5	13.0	9.7	8.5	9.5	13.8
271	-3467.21	-3447.50	44.9	13.0	11.7	8.9	7.8	13.7

Figure 1: 6-Group Substance Use Trajectories (022220, Iorder 2) (n=274)

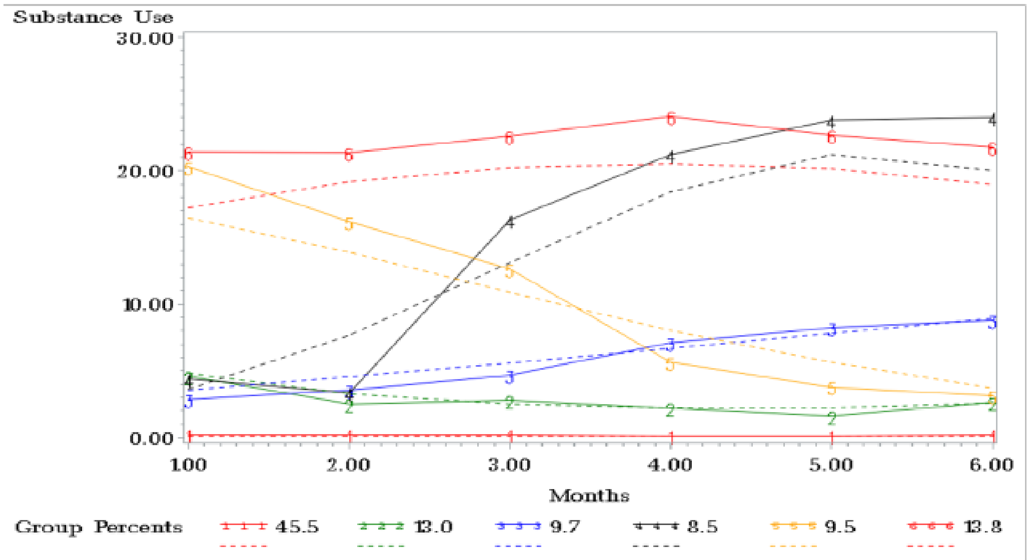
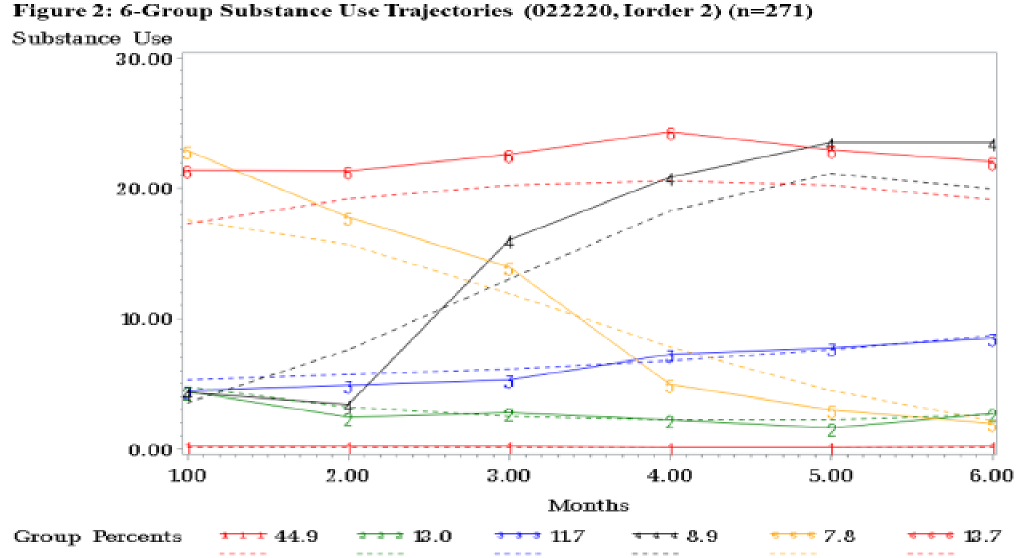


Figure 2: 6-Group Substance Use Trajectories (022220, Iorder 2) (n=271)



Sensitivity Analysis for Group-based Trajectory Model Selection

Five-Group Models

To further test the models selected, further analyses was run to determine the model fit statistics, polynomial ordering, and predictor time-stable variables for five- and seven-group models. For the five-group model, the percentage within each group, posterior probabilities, and OCC are all acceptable. However, the BIC is greater than the final six-group model and thus is not a preferable model (Table 4). Table 5 and 6 display the parameters and diagnostics for a potential five-group model. Further examining the five-group model reveals there is no high use group, an important interpretable trajectory in the final model (Figure 3). Examining the predictor variables across the five-group model revealed that there would be some differences compared to the six-group model (Table 7). Having a high school diploma and being a hard drug user become significant, whereas lifetime prior treatment, self-esteem, and self-determination are not significant. Despite these differences examined across trajectory models, the five-group model is still not a better model than the final six-group model due to the BIC and the lack of the high use group in any model, with or without predictor variables (Figure 4 to 7).

Table 4: GBTM Model Selection using BIC and Estimated Group Proportions (n=275)

# of Groups	Order	Iorder	BIC (N=1650)[1]	BIC (N=275)[2]	Estimated Group Proportions 1	2	3	4	5	6	7	8
2	22	2	-4411.52	-4402.56	59.3	40.7						
3	222	2	-3938.08	-3925.54	48.8	26.0	25.1					
4	2222	2	-3740.90	-3724.77	46.3	19.6	12.3	21.8				
5	22222	2	-3647.31	-3627.60	45.9	13.2	12.8	7.8	20.3			
6	222222	2	-3490.98	-3467.68	45.8	12.8	11.5	8.7	7.7	13.5		
7	2222222	2	-3481.91	-3455.03	22.2	24.3	12.3	11.4	8.7	7.6	13.5	
8	22222222	2	-3491.51	-3461.05	32.9	13.9	8.0	10.9	8.7	10.6	14.9	0.0
5	**02121**	**2**	-3635.67	-3619.54	45.8	13.3	12.9	7.7	20.3			

BIC[1]=overall sample size; BIC[2]=subject sample size

Table 5: GBTM with 5-Group Substance Use Trajectories (n=275)

Group	Parameter Estimate	t-statistic	P-value
Group1			
Intercept	-1.43869	-13.843	<0.001
Group 2			
Intercept	2.66104	15.102	<0.001
Linear	-0.75109	-6.023	<0.001
Quadratic	0.08985	4.996	<0.001
Group 3			
Intercept	1.90420	20.573	<0.001
Linear	0.11074	5.253	<0.001
Group 4			
Intercept	3.43640	28.152	<0.001
Linear	-0.05340	-0.529	0.597
Quadratic	-0.05516	-3.126	0.002
Group 5			
Intercept	3.01074	95.828	<0.001
Linear	0.05924	7.781	<0.001

Table 6: GBTM Diagnostics (n=275)

Group	Proportion in Group	Average Posterior Probability	Odds of Correct Classification
Group 1	0.46	0.99	84.70
Group 2	0.13	0.92	71.61
Group 3	0.13	0.94	107.90
Group 4	0.08	0.93	153.06
Group 5	0.20	0.97	129.58

Figure 3: 5-Group Trajectories without Covariates

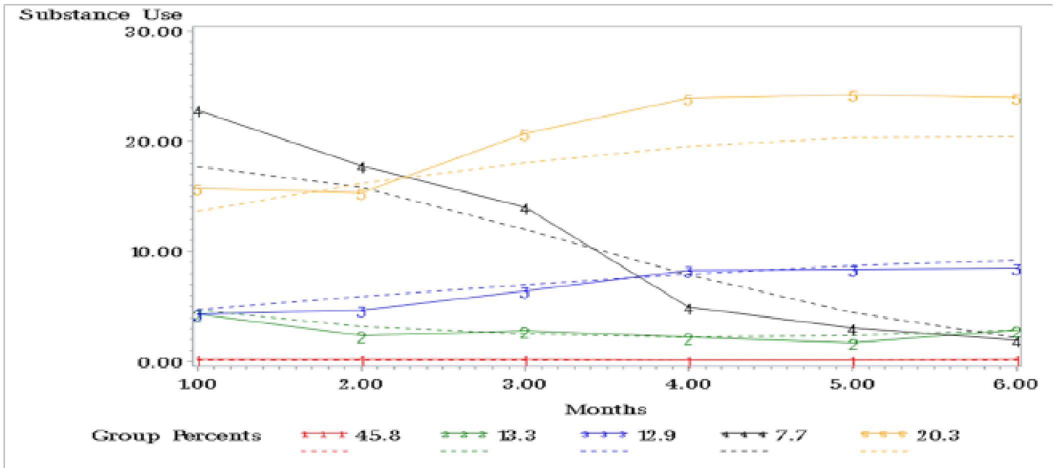


Table 7: Bivariate Statistics of the Time-Stable Predictors by Substance Use Trajectories for 5-groups

	Substance Use Trajectory Groups					
Predictor	Group 1	Group 2	Group 3	Group 4	Group 5	P-value
Demographics						
Female	34 (26.8)	11 (29.7)	11 (32.4)	7 (33.3)	22 (39.3)	0.562
Nonwhite	102 (80.3)	25 (67.6)	23 (69.7)	18 (85.7)	46 (82.1)	0.251
Stable housing	**109 (85.8)**	**26 (70.3)**	**27 (79.4)**	**12 (57.1)**	**40 (71.4)**	**0.014**
High school diploma	50 (39.4)	17 (45.9)	17 (50.0)	9 (42.9)	12 (21.4)	0.042
Committed rel.	71 (55.9)	22 (59.5)	20 (58.8)	7 (33.3)	34 (60.7)	0.270
Unemployed	65 (51.2)	19 (51.4)	13 (38.2)	14 (66.7)	36 (64.3)	0.107
Age	35.7 ± 11.7	34.0 ± 11.7	35.3 ± 12.0	34.2 ± 12.0	32.9 ± 10.7	0.647
Prior substance treatment and use history						
Lifetime prior treatment	54 (42.5)	22 (59.5)	15 (44.1)	14 (66.7)	31 (55.4)	0.108
Initiated 15 and under	**72 (56.7)**	**25 (67.6)**	**20 (58.8)**	**15 (71.4)**	**46 (82.1)**	**0.017**
Hard drug use	53 (41.7)	22 (59.5)	18 (52.9)	13 (61.9)	37 (66.1)	0.022
Recent IV drug user	7 (5.5)	3 (8.1)	5 (14.7)	2 (9.5)	7 (12.5)	0.378
Consequences of use	**126 ± 10.7**	**17.9 ± 13.5**	**16.2 ± 11.5**	**23.5 ± 14.7**	**17.7 ± 12.8**	**<0.001**
Family/peer drug use	**1.6 ± 0.7**	**1.8 ± 0.7**	**1.8 ± 0.7**	**2.1 ± 1.0**	**2.1 ± 0.8**	**<0.001**
ASI alcohol severity	0.2 ± 0.1	0.2 ± 0.2	0.3 ± 0.1	0.2 ± 0.2	0.2 ± 0.2	0.479
ASI drug severity	**0.1 ± 0.1**	**0.1 ± 0.1**	**0.1 ± 0.1**	**0.2 ± 0.2**	**0.2 ± 0.2**	**<0.001**
Criminal justice						
Drug testing condition	**102 (80.3)**	**26 (70.3)**	**21 (61.8)**	**17 (81.0)**	**34 (60.7)**	**0.031**
Drug treatment cond.	43 (33.9)	15 (40.5)	10 (29.4)	11 (52.4)	20 (35.7)	0.452
Drug instant offense	53 (41.7)	20 (54.1)	15 (44.1)	7 (33.3)	26 (46.4)	0.577
Risk score	4.1 ± 2.2	4.0 ± 2.0	4.1 ± 1.9	5.1 ± 1.7	4.6 ± 1.9	0.225
Probation sentence	41.1 ± 97.0	28.1 ± 22.4	23.9 ± 16.5	23.6 ± 12.6	25.9 ± 15.1	0.454
Days on probation	73.6 ± 322.0	31.6 ± 69.3	27.7 ± 61.3	35.7 ± 78.4	43.9 ± 113.6	0.742
Psychosocial						
Risk mental disorders	9 (7.1)	4 (10.8)	5 (14.7)	6 (28.6)	8 (14.3)	0.061
Risk severe mental disord.	41 (32.5)	12 (32.4)	14 (41.2)	11 (52.4)	25 (44.6)	0.275
Self-esteem	36.4 ± 7.1	34.6 ± 6.7	35.7 ± 8.0	31.3 ± 10.7	34.7 ± 8.8	0.077
Decision-making	37.5 ± 4.6	37.0 ± 4.4	36.4 ± 4.1	36.9 ± 4.8	36.2 ± 6.1	0.523
Hostility	**25.4 ± 6.1**	**27.0 ± 7.0**	**26.4 ± 7.8**	**30.5 ± 6.9**	**28.3 ± 7.0**	**0.006**
Risk taking	**26.6 ± 5.3**	**30.2 ± 7.7**	**29.6 ± 6.2**	**30.3 ± 7.1**	**30.1 ± 5.8**	**<0.001**
Recognition	**25.9 ± 8.7**	**29.2 ± 8.8**	**27.6 ± 9.4**	**33.5 ± 9.4**	**29.2 ± 9.8**	**0.004**
Social support	3.9 ± 1.0	3.7 ± 1.0	3.8 ± 1.1	3.3 ± 1.2	3.8 ± 1.1	0.199
Self-determination	3.9 ± 0.8	3.7 ± 0.7	3.9 ± 0.9	3.5 ± 0.9	3.6 ± 0.9	0.058
Additional controls						
Study arms						
MI	42 (33.1)	10 (27.0)	11 (32.4)	5 (23.8)	20 (35.7)	0.828
MAPIT	38 (29.9)	16 (43.2)	12 (35.3)	9 (42.9)	19 (33.9)	0.542
SAU	47 (37.0)	11 (29.7)	11 (32.4)	7 (33.3)	17 (30.4)	0.880
Dallas	**91 (71.7)**	**23 (62.2)**	**17 (50.0)**	**9 (42.9)**	**27 (48.2)**	**0.006**

Figure 4: 5-Group trajectories including all time-stable covariates

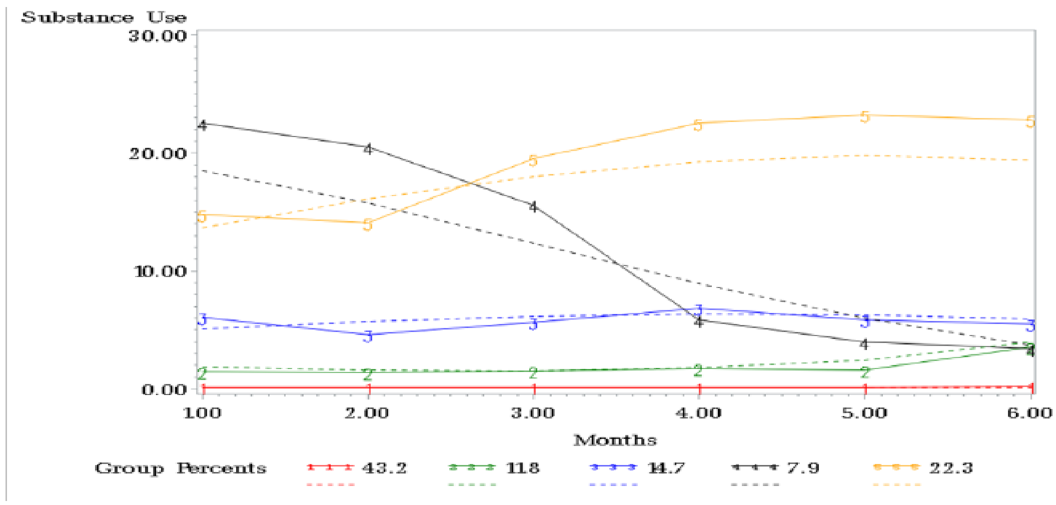


Figure 5: 5-Group trajectories including significant time-stable covariates

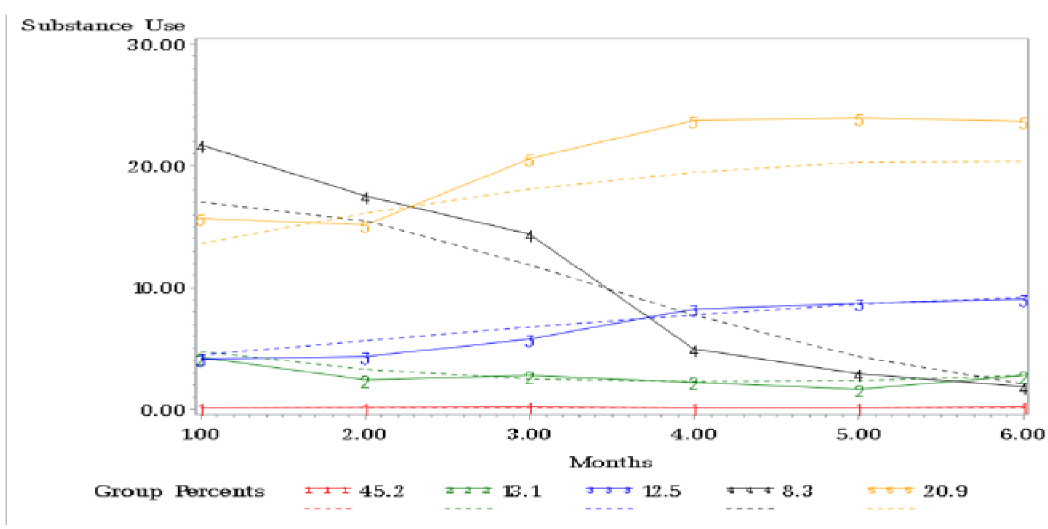


Figure 6: 5-Group trajectories including significant time-varying covariates

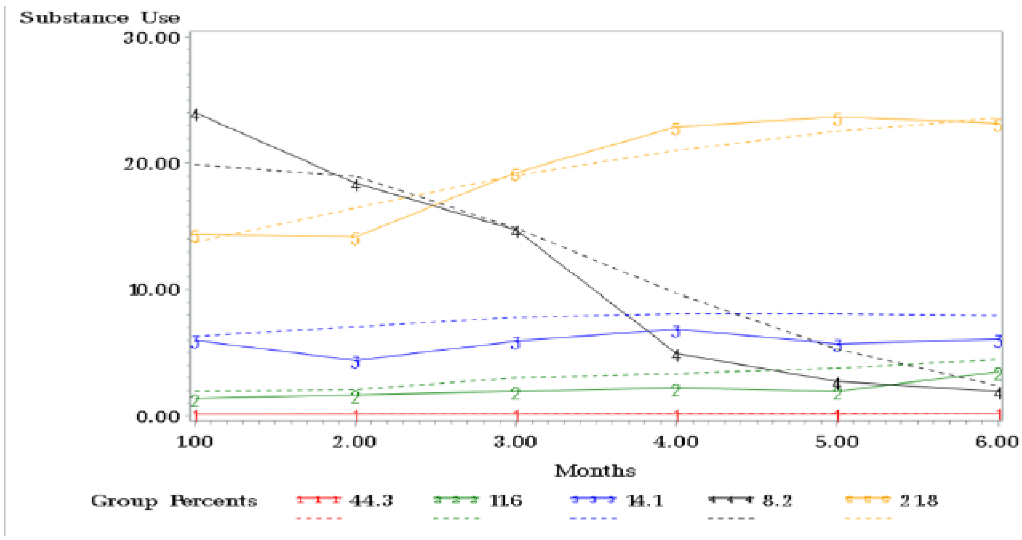
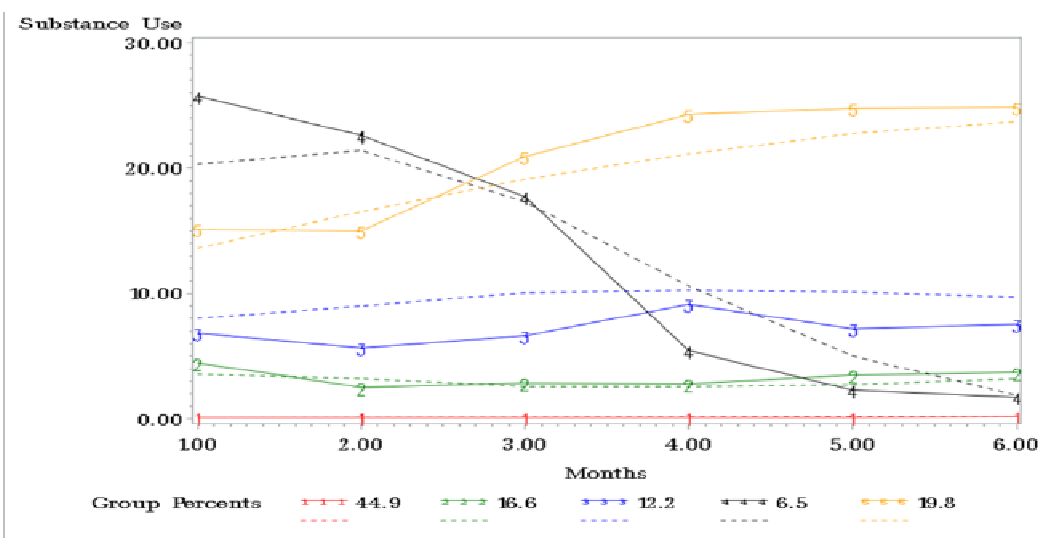


Figure 7: 5-Group trajectories including significant time-stable and time-varying covariates



Seven-Group Models

For the seven-group model, without covariates, the percentage within each group, posterior probabilities, and OCC are all acceptable. However, the BIC within one point of the final six-group model and thus is not an improvement over the six-group model (Table 8). Table 9 and 10 display the parameters and diagnostics for a potential seven-group model. There are some differences in predictor variables for the seven-group model (Table 11). Having a high school diploma, being unemployed, and being a hard drug user become significant, whereas self-esteem and self-determination are not significant. Despite these differences, the seven-group model is not the preferred model because of the BIC and the instability of the trajectories once covariates are added (Figures 8 to 11). The seven-group model would not converge when only the significant time-stable predictors are included and group seven has no one represented in the trajectory group when the time-varying predictors are included due to unsuccessful convergence.

Table 8: GBTM Model Selection using BIC and Estimated Group Proportions (n=275)

# of Groups	Order	Iorder	BIC (N=1650)[1]	BIC (N=275)[2]	Estimated Group Proportions							
					1	2	3	4	5	6	7	8
2	22	2	-4411.52	-4402.56	59.3	40.7						
3	222	2	-3938.08	-3925.54	48.8	26.0	25.1					
4	2222	2	-3740.90	-3724.77	46.3	19.6	12.3	21.8				
5	22222	2	-3647.31	-3627.60	45.9	13.2	12.8	7.8	20.3			
6	222222	2	-3490.98	-3467.68	45.8	12.8	11.5	8.7	7.7	13.5		
7	2222222	2	-3481.91	-3455.03	22.2	24.3	12.3	11.4	8.7	7.6	13.5	
8	22222222	2	-3491.51	-3461.05	32.9	13.9	8.0	10.9	8.7	10.6	14.9	0.0
7	**0021110**	**2**	-3476.71	-3457.90	30.6	16.2	11.9	9.6	9.3	9.2	13.3	

BIC[1]=overall sample size; BIC[2]=subject sample size

Table 9: GBTM with 7-Group Substance Use Trajectories (n=275)

Group	Parameter Estimate	t-statistic	P-value
Group 1			
Intercept	-2.94	-5.58	<0.001
Group 2			
Intercept	-0.44	-2.09	0.0364
Group 3			
Intercept	2.69	15.52	<0.001
Linear	-0.73	-5.75	<0.001
Quadratic	0.08	4.48	<0.001
Group 4			
Intercept	1.51	13.99	<0.001
Linear	0.17	7.12	<0.001
Group 5			
Intercept	3.60	63.46	<0.001
Linear	-0.31	-15.92	<0.001
Group 6			
Intercept	2.07	31.29	<0.001
Linear	0.24	16.36	<0.001
Group 7			
Intercept	0.24	16.36	<0.001

Table 10: GBTM Diagnostics (n=275)

Group	Proportion in Group	Average Posterior Probability	Odds of Correct Classification
Group 1	0.31	0.88	16.42
Group 2	0.16	0.88	39.60
Group 3	0.12	0.94	124.03
Group 4	0.10	0.94	154.06
Group 5	0.09	0.93	121.46
Group 6	0.09	0.96	234.74
Group 7	0.13	0.95	123.44

Table 11: Bivariate Statistics of the Time-Stable Predictors by Substance Use Trajectories for 7-groups

	Substance Use Trajectory Groups							
Predictor	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	P-value
Demographics								
Female	22 (23.7)	14 (37.8)	9 (28.1)	8 (30.8)	8 (32.0)	10 (40.0)	14 (37.8)	0.537
Nonwhite	74 (79.6)	31 (83.8)	20 (62.5)	16 (64.0)	22 (88.0)	22 (88.0)	29 (78.4)	0.084
Stable housing	**80 (86.0)**	**32 (86.5)**	**22 (68.8)**	**21 (80.8)**	**15 (60.0)**	**17 (68.0)**	**27 (73.0)**	**0.037**
High school diploma	**36 (38.7)**	**16 (43.2)**	**14 (43.8)**	**16 (61.5)**	**9 (36.0)**	**6 (24.0)**	**8 (21.6)**	**0.038**
Committed rel.	49 (52.7)	23 (62.2)	19 (59.4)	4 (53.8)	10 (40.0)	18 (72.0)	21 (56.8)	0.382
Unemployed	**48 (51.6)**	**17 (45.9)**	**17 (53.1)**	**7 (26.9)**	**17 (68.0)**	**19 (76.0)**	**22 (59.5)**	**0.013**
Age	35.5 ± 11.76	35.7 ± 11.4	35.1 ± 12.1	34.8 ± 10.7	33.6 ± 12.0	30.1 ± 10.8	35.4 ± 11.4	0.548
Prior substance treatment and use history								
Lifetime prior treatment	**38 (40.9)**	**18 (48.6)**	**20 (62.5)**	**10 (38.5)**	**16 (64.0)**	**10 (40.0)**	**24 (64.9)**	**0.048**
Initiated 15 and under	**53 (57.0)**	**21 (56.8)**	**22 (68.8)**	**13 (50.0)**	**18 (72.0)**	**23 (92.0)**	**28 (75.7)**	**0.010**
Hard drug use	**32 (34.4)**	**22 (59.5)**	**21 (65.6)**	**14 (53.8)**	**16 (64.0)**	**16 (64.0)**	**22 (59.5)**	**0.005**
Recent IV drug user	6 (6.5)	1 (2.7)	3 (9.4)	4 (15.4)	2 (8.0)	3 (12.0)	5 (13.5)	0.522
Consequences of use	**11.3 ± 10.5**	**14.6 ± 10.7**	**20.2 ± 13.8**	**15.6 ± 12.2**	**22.5 ± 14.2**	**14.2 ± 11.4**	**18.9 ± 12.8**	**<0.001**
Family/peer drug use	**1.6 ± 0.7**	**1.7 ± 0.7**	**1.9 ± 0.8**	**1.7 ± 0.7**	**2.1 ± 0.9**	**1.2 ± 0.9**	**2.1 ± 0.7**	**0.001**
ASI alcohol severity	0.2 ± 0.1	0.3 ± 0.2	0.2 ± 0.2	0.3 ± 0.1	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.2	0.234
ASI drug severity	**0.1 ± 0.1**	**0.1 ± 0.1**	**0.2 ± 0.2**	**0.1 ± 0.1**	**0.2 ± 0.1**	**0.2 ± 0.1**	**0.1 ± 0.1**	**<0.001**
Criminal justice								
Drug testing condition	**81 (87.1)**	**24 (64.9)**	**21 (65.6)**	**19 (73.1)**	**21 (84.0)**	**12 (48.0)**	**22 (59.5)**	**<0.001**
Drug treatment cond.	32 (34.4)	12 (32.4)	14 (43.8)	6 (23.1)	15 (60.0)	8 (32.0)	12 (32.4)	0.140
Drug instant offense	37 (39.8)	18 (48.6)	16 (50.0)	12 (46.2)	10 (40.0)	9 (36.0)	19 (51.4)	0.792
Risk score	4.2 ± 2.2	3.9 ± 2.3	4.4 ± 1.9	4.2 ± 2.0	4.7 ± 2.0	4.3 ± 1.8	4.6 ± 1.9	0.694
Probation sentence	46.6 ± 112.6	25.9 ± 14.8	28.3 ± 23.9	22.4 ± 13.3	25.8 ± 17.1	23.0 ± 10.6	27.5 ± 16.9	0.418
Days on probation	86.8 ± 367.8	34.5 ± 124.9	32.0 ± 71.9	17.7 ± 15.0	47.2 ± 97.6	51.0 ± 117.4	37.2 ± 104.0	0.765
Psychosocial								
Risk mental disorders	5 (5.4)	5 (13.9)	3 (9.4)	5 (19.2)	6 (24.0)	3 (12.0)	5 (13.5)	0.165
Risk severe mental disord.	31 (33.3)	11 (30.6)	10 (31.3)	12 (46.2)	12 (48.0)	10 (40.0)	17 (45.9)	0.524
Self-esteem	36.4 ± 7.0	36.5 ± 7.3	34.4 ± 7.1	35.2 ± 8.4	31.3 ± 9.6	36.5 ± 9.5	34.4 ± 8.2	0.105
Decision-making	37.4 ± 4.7	37.8 ± 4.0	36.7 ± 4.7	36.4 ± 4.0	36.6 ± 4.9	36.7 ± 5.9	36.3 ± 6.0	0.780
Hostility	**25.3 ± 6.1**	**25.9 ± 6.2**	**27.0 ± 7.3**	**26.0 ± 7.5**	**30.0 ± 7.0**	**29.0 ± 6.8**	**27.7 ± 7.4**	**0.027**
Risk taking	**26.3 ± 5.5**	**27.3 ± 4.9**	**30.4 ± 8.1**	**26.0 ± 7.5**	**30.0 ± 7.0**	**29.0 ± 6.8**	**27.7 ± 7.4**	**0.001**
Recognition	**25.4 ± 8.9**	**27.1 ± 7.7**	**30.2 ± 9.2**	**26.8 ± 9.4**	**33.2 ± 8.8**	**26.3 ± 9.8**	**30.7 ± 9.5**	**0.001**
Social support	3.8 ± 1.1	4.2 ± 0.8	3.7 ± 0.9	3.7 ± 1.1	3.6 ± 1.2	3.8 ± 1.3	3.7 ± 1.0	0.411
Self-determination	3.9 ± 0.8	3.8 ± 0.8	3.7 ± 0.7	3.9 ± 1.0	3.5 ± 0.9	3.8 ± 0.8	3.5 ± 0.9	0.178
Additional controls								
Study arms								
MI	35 (37.6)	8 (21.6)	9 (28.1)	10 (38.5)	5 (20.0)	5 (20.0)	16 (43.2)	0.154
MAPIT	26 (28.0)	14 (37.8)	12 (37.5)	9 (34.6)	11 (44.0)	12 (48.0)	10 (27.0)	0.421
SAU	32 (34.4)	15 (40.5)	11 (34.4)	7 (26.9)	9 (36.0)	8 (32.0)	11 (29.7)	0.946
Dallas	**71 (76.3)**	**23 (62.2)**	**18 (56.3)**	**16 (61.5)**	**12 (48.0)**	**9 (36.0)**	**18 (48.6)**	**0.003**

Figure 8: 7-Group Trajectories without Covariates

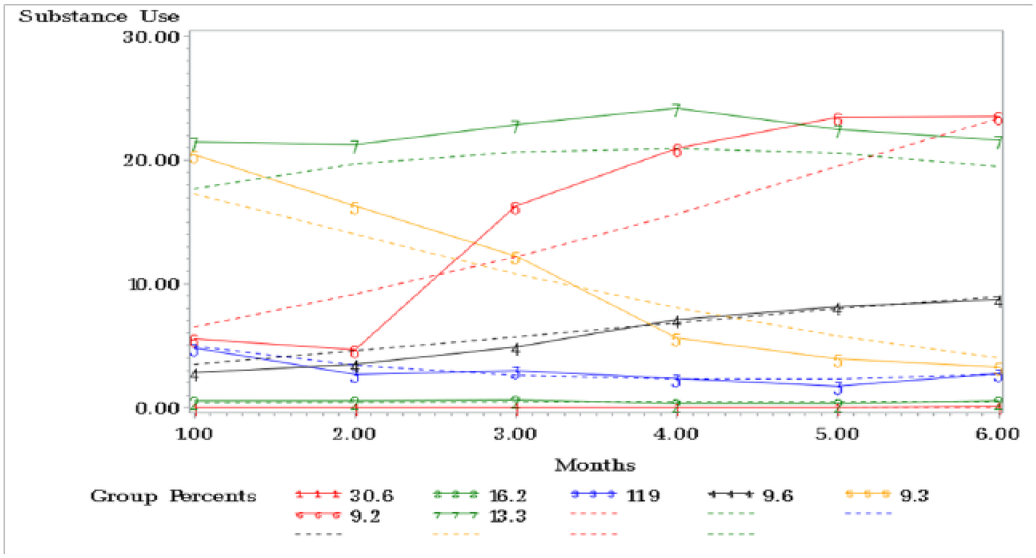
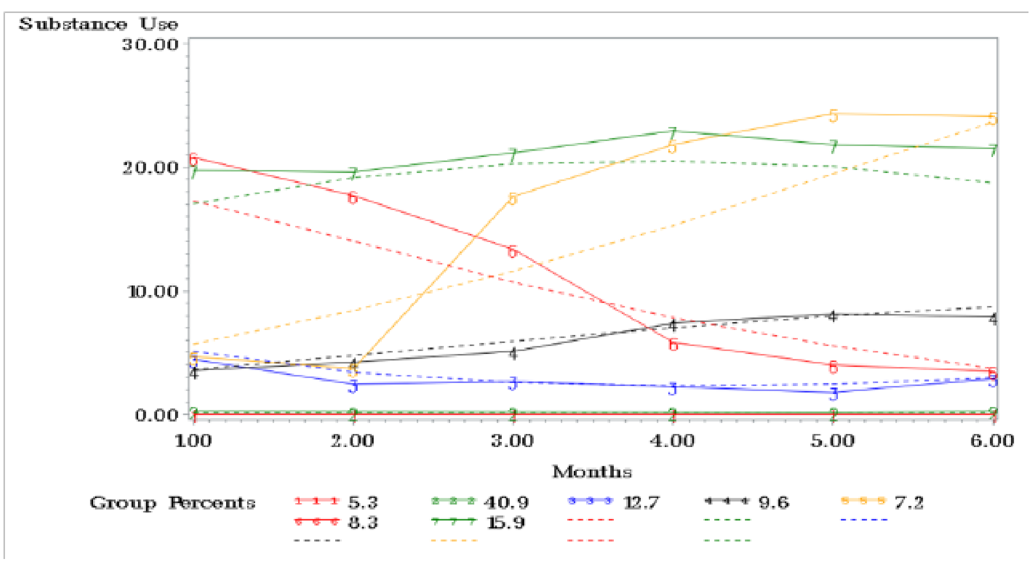


Figure 9: 7-Group trajectories including all time-stable covariates



Seven-Group trajectories including significant time-stable covariates
Wouldn't converge

Figure 10: 7-Group trajectories including time-varying covariates

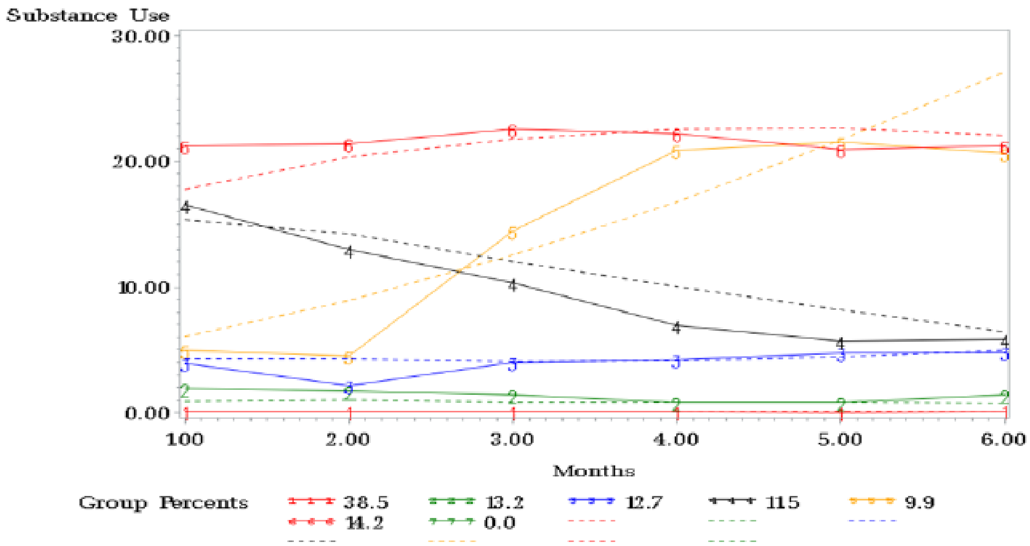
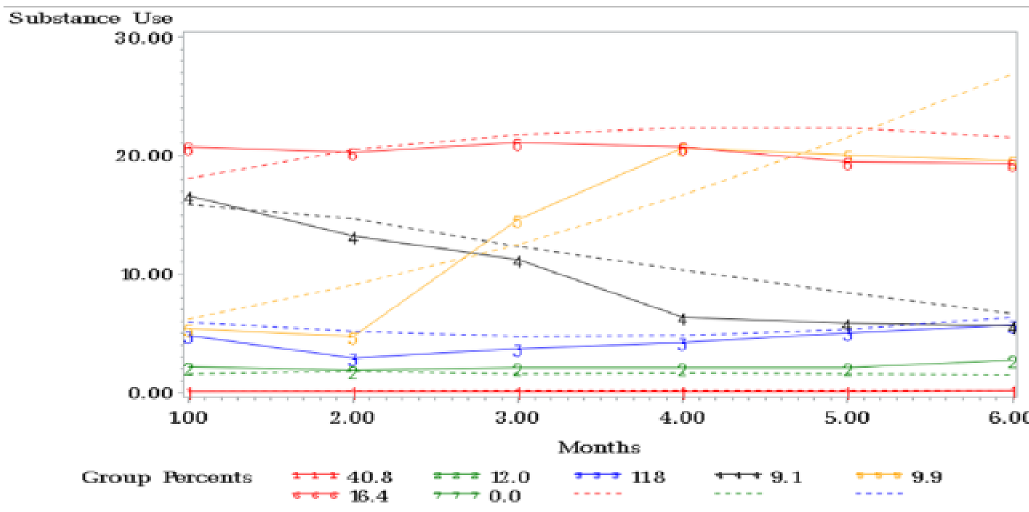


Figure 11: 7-Group trajectories including significant time-stable and time-varying covariates



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BIOGRAPHY

Jennifer Lerch received her Bachelor of Science degree in Political Science and Sociology from Shepherd University in 2005 and her Masters of Arts in Justice, Law, and Crime Policy from George Mason University in 2009. Jennifer is a Research Associate at George Mason University's Center for Advancing Correctional Excellence (ACE!) and has led the evaluation, data collection, data management, and produced important study findings on several large-scale projects. She has over ten years' experience conducting evaluations, questionnaires, onsite field research, and collecting and analyzing administrative data. Jennifer has been the Principal Investigator on several projects including two research evaluations examining young adults. One effort is a Bureau of Justice Assistance funded evaluation of the Hidalgo County Emerging Adult Strategy (HCEAS), a randomized controlled trial design to examine the effect a specialty court for emerging adults on recidivism. The second is a National Institute of Justice funded research study examining the effectiveness of a jail-based specialized curriculum for emerging adults reentering the community using a randomized controlled design. Jennifer was one of the project managers for MAPIT. She oversaw data collection and management for this project, as well as publishing the main findings from this study. She also has expertise on the risk-need-responsivity model and has trained community providers and criminal justice practitioners across the country on this evidence-based practice. Jennifer has co-authored several peer-reviewed publications and regularly presents her work at national and international conferences.