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Polysubstance Use Patterns among Justice-Involved Individuals Who Use Opioids

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Abstract

Aim: The current study explores pre-incarceration polysubstance patterns among a justice-involved population who use opioids.

Design: Setting: Data from prison and jail substance use programing in the state of Kentucky from 2015–2017 was examined.

Participants: A cohort of 6,569 individuals who reported both pre-incarceration use of opioids and reported the use of more than one substance per day.

Measurements: To determine the different typologies of polysubstance use involving opioids, latent profile analysis of the pre-incarceration thirty-day drug use of eight substances was conducted. Multinomial logistic regression predicted latent profile membership.

Findings: Six unique profiles of polysubstance use involving opioids and other substances were found; Primarily Alcohol (9.4%), Primarily Heroin (19.0%), Less Polysubstance Use (34.3%), Tranquilizer Polysubstance Use (16.3%), Primarily Buprenorphine (7.8%), and Stimulant-Opioid (13.2%). Profiles differed by rural/urban geography, injection drug use, physical, and mental health symptoms.

Conclusion: Findings indicate the heterogeneity of opioid use among a justice-involved population. More diverse polysubstance patterns may serve as a proxy to identifying individuals with competing physical and mental health needs. Future interventions could be tailored to polysubstance patterns during the period of justice-involvement.

Keywords

Opioid; polysubstance use; latent profile analysis; criminal justice

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No conflict declared.

Data availability statement
The data that support the findings of this study can be made available on request from the corresponding author, AMB. The data are not publicly available due to confidentiality of participants.

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Introduction

Opioid use has reached epidemic levels, impacting individuals as well as criminal justice and healthcare systems across the United States. Since 1999, the number of overdose mortalities and prevalence of opioid use disorders increased rapidly, leading U.S. health leaders to call a public health emergency and recognition of the crisis as an opioid epidemic (Han et al., 2015; HHS Press, 2017; Scholl et al., 2018). Nearly one-third of opioid related overdoses are due to polysubstance use (PSU), a pattern of substance use when two or more substances being used in the same timeframe (i.e. regular-interval PSU) or simultaneously (i.e. same time). Specific to the current research PSU refers to the co-use of opioids with other drugs in a given timeframe (Mattson et al., 2018; Ruhm, 2017). Individuals who engage in PSU tend to be younger, with lower levels of education, and more extensive criminal histories (Darke & Hall, 1995; Martinotti et al., 2009). Research has also found associations of certain PSU patterns with increased HIV and HCV serostatus and risk factors such as syringe sharing (Harrell et al., 2012; Meacham et al., 2015).

PSU is particularly pronounced among individuals with more severe substance use disorders, including justice-involved populations. Compared to the general public, justice-involved populations have more severe drug use histories (Mumola & Karberg, 2006) including high rates of PSU (Kubiak, 2004; Lo & Stephens, 2000) and more severe opioid use disorder (Winkelman et al., 2018). Post-release from prison, individuals are at increased risk of overdose (Binswanger et al., 2007). Among formerly incarcerated individuals 56% of overdose deaths involved PSU, with opioid and cocaine PSU most common (Binswanger et al., 2013). Previous research that has examined patterns of PSU involving opioids has not done so explicitly among a justice-involved population despite this populations elevated risk for adverse outcomes. Limited research has examined justice-involvement as an independent correlate and has found more extensive PSU patterns associated with higher justice-involvement (Betts et al., 2016; Fernández-Calderón et al., 2015; Green et al., 2011). Explicit examination of this population’s PSU patterns is necessary in order to provide supportive treatment during incarceration as well as reentry and post-release treatment services.

In this study, a latent profile analysis (LPA) explores substance use behaviors of justice-involved persons who report use of opioids with other substances. The current research expands previous research by providing detailed insights, using latent profile analysis, to the PSU patterns among a justice-involved population who use opioids. Given high rates of opioid use, and that known estimates of PSU among justice-involved persons explore only prevalence and not patterns, the current research describes the PSU patterns of people who use opioids prior to their entrance to a prison and jail-based substance use treatment program. Persons who use opioids are not a homogenous group and assuming that all individuals have similar substance-using patterns undermines the potential for successful treatment and reentry outcomes.

Methods

Sample

Data from the current study were collected from the Criminal Justice Kentucky Treatment Outcome Study (CJKTOS). The study is a state-mandated treatment outcome study of the Department of Corrections' (DOC) substance abuse programing (SAP), ongoing since 2005 in conjunction with the University of Kentucky's Center on Drug and Alcohol Research. The SAP is available to individuals in Kentucky prison, jails, and community custody programs with a self-report of substance use history and 24-months remaining before parole or release. The program is 6-months in duration and follows a therapeutic community model of treatment (DeLeon, 2000). Within the first two weeks of entering SAP, a baseline assessment is given by trained DOC staff using computer assisted personal interview (CAPI) software. Consent to baseline assessment is part of DOC consent to treatment. The study is approved by the University Institutional Review Board. A federal certificate of confidentiality was obtained.

Inclusion criteria for the current analyses were (1) participation in prison or jail-based SAP in 2015–2017, (2) self-reported use of an opioid (i.e. heroin, nonmedical use of buprenorphine or methadone, or nonmedical use of opioids) in the 12-months prior to incarceration, and (3) self-reported use of more than one substance on a given day in the month prior to incarceration. These criteria resulted in a final sample size of 6,569. Individuals were incarcerated a median of 1.16 years before entering the SAP and receiving their baseline assessment.

The state of Kentucky was dealing with staggering rates of opioid use and overdose during this time period (Scholl et al., 2018), including increasing heroin and injection drug use among justice populations (Bunting et al., 2020). In 2017, Kentucky was among the states with the highest rates of overdose at a rate of 37.2 per 100,000 persons, representing a significant increase from the year prior (Scholl et al., 2018) and continuing the trend of increasing opioid overdose deaths since 1999 (CDC Wonder). Rural Appalachian Kentucky was particularly affected (Keyes et al., 2014), and aggressive marketing of OxyContin, the presence of 'pill mills,' declining employment related to the state's coal economy, and high burden of disease and work-related injuries contributed to Kentucky's risk (Jonas et al., 2012; Quinones, 2015; Slavova et al., 2017). As a result, the number of individuals incarcerated during this period increased (Bronson & Carson, 2019; Carson, 2018) and prerelease injectable naltrexone was made available to eligible individuals who completed the SAP.

Variables

Latent profile indicators—The baseline assessment contained a variety of demographic, criminal history, mental and physical health, and substance use questions. Substance use questions were drawn from the Addiction Severity Index (McLellan et al., 1992). Individuals were first asked if they used a substance in the 12-months prior to their incarceration. If an individual indicated they used a substance, they were then asked the number of days of use of the substance in the 30-days prior to incarceration. To enhance interpretability and stability of latent profiles, following previous studies and statistical practices (Kuramoto et al., 2011; Monga et al., 2007), only substances where a minimum of 20% of the sample reported use were included for analysis. This resulted in the exclusion of barbiturates (5.7%), hallucinogens (7.2%), inhalants (2.9%), nonmedical use of methadone (14.8%), and synthetic drugs (16.8%). Additional models were examined including substance use indicators that had above 10% prevalence (e.g. synthetics, methadone) but model fit was poor, as indicated by lower entropy values and larger Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values (results not shown). Latent profiles were created based on 30-day use of alcohol, cocaine, marijuana, heroin, nonmedical use of buprenorphine, nonmedical use of prescription opioids (NMPO), amphetamines (nonmedical use of amphetamines and/or methamphetamine), and nonmedical use of tranquilizers. Questions regarding opioids, methadone, buprenorphine, tranquilizers, and amphetamines were presented to participants as “[substance] not prescribed for you.”

Covariates—Several sociodemographic variables were measured to include age, years of education, gender, race, unemployment in the 30 days prior to incarceration, and homelessness in the 12 months prior to incarceration. The county an individual lived in prior to incarceration was coded utilizing a rural-urban coding scheme (Ingram & Franco, 2014) such that counties with populations of 250,000 or more were coded as 0 = urban and remaining counties (250,000 or less) were coded as 1 = rural. Pre-incarceration financial strain was measured on an 8-item summative scale (α=.87; Range:0–8) of economic hardship adapted from the Survey of Income and Program Participation to include difficulty meeting needs of food, housing, clothing, and medical care (Beverly, 2001). Injection drug use (IDU) was a dichotomous variable measuring lifetime IDU, such that individuals reported ever having injected drugs (1 = yes).

Individual’s physical health was measured by three variables. A dichotomous variable measured if individuals reported chronic pain where pain persisting or recurring three months or longer (1 = yes), self-reported HCV status, and a continuous variable from the Behavioral Risk Factor Surveillance System (BRFSS) measuring the number of self-reported poor physical health days in the 30-days prior to incarceration (CDC, 2019; Hennessy et al., 1994).

Anxiety and depressive symptoms in the 12-months prior to incarceration were measured using a version of the Generalized Anxiety Disorder-7 (GAD-7; 25) (α= .97; Range:0–7) and the Patient Health Questionnaire-9 (PHQ-9; 26) (α=.94; Range: 0–9) which utilized modified dichotomous questionnaire items (Logan et al., 2016). Three questions measuring stress-related health consequences were examined (Logan et al., 2016). These questions ask if participants used (1) illegal drugs, (2) alcohol, and/or (3) prescription drugs to reduce stress, anxiety, worry or fear in the week prior to their incarceration. Answers were collapsed so that individuals reporting response of ‘most of’ or ‘all of the time’ were compared to those reporting ‘none of’ or ‘some of the time.’ A validated continuous variable measuring the number of self-reported poor mental health days in the 30-days prior to incarceration was also included (CDC, 2019; Hennessy et al., 1994).

A continuous variable measuring self-reported lifetime number of criminal convictions was included. A series of dichotomous variables were created to measure prior 12-month arrests according to offense type (drug, violent, property). There were other crimes that did not fit one of the three categories (e.g. receiving stolen property, 5.6%), which were excluded. Individuals could report prior arrests for more than one type of crime.

Missing data—Data were missing for 9 individuals- 4 were missing data on their lifetime number of convictions and 5 were missing values for lifetime IDU history. For convictions, mean imputation was used. For IDU, individuals were conservatively assigned a value of 0, indicating no lifetime IDU history. Models were run with and without the 9 individuals, and no differences were found.

Analysis

To consider the heterogeneity of PSU populations, researchers have advocated for the use of latent class analysis (e.g. Agrawal et al., 2007; Schwartz et al., 2010). Previous research has utilized dichotomous latent class indicators, which capture regular interval PSU in the time-period analyzed, with the majority of studies utilizing previous 30-day time periods (e.g. Fong et al., 2015; Harrell et al., 2012; Monga et al., 2007; Patra et al., 2009). Only one known study used 30-day continuous indicators of substance use (Parsons et al., 2014), and the current research advocates further examination of PSU patterns using continuous indicators as necessary in order to provide more detailed insights to PSU patterns. Continuous LPA provides more accurate insight into risk of PSU through details on the likelihood of overlap of substance use within a month, rather than if use of two or more substances merely occurs.

LPA was utilized to determine the unobserved patterns of the data utilizing the 30-day reported substance use indicators to form subgroups. The eight continuous substance use variables were entered into the LPA model. A simple model (1-class) was fit first and classes were then incrementally increased until selection criteria began to decline. Selection criteria were based on standard fit statistics of AIC, BIC, entropy, and likelihood ratio tests. Selection was also guided by best practices and substantive criteria, such as model ideals of parsimony, homogony, separation, and meaningfulness of profiles. In order to ensure the best fitting model was selected, cross-validation and model convergence was tested by randomly varying the starting points for the maximum likelihood. A model is considered identified when classes consistently converge regardless as to maximum likelihood starting point (Collins & Lanza, 2010).

Individuals were assigned to profiles based on their most likely profile membership for examination of bivariate associations. Profile membership is independent in that individuals cannot belong to more than one profile. Chi-square tests and ANOVA were used to determine if profiles differed from each other on associated variables. To examine covariate effects (i.e. variables influencing profile membership), the one-step method was used such that covariates were estimated simultaneously with latent profiles (Kamata et al., 2018). Latent mixture models with covariates are conceptually similar to multinomial regression models in that covariates of interest serve as predictors of most probable latent profile membership. By estimating the models simultaneously (allowing the latent profile model and covariate multinomial logistic regression to estimate freely at the same time) measurement error related to profile assignment is avoided (Kamata et al., 2018). A model was estimated including all sociodemographic, physical, and mental health variables. Added to this model, each criminal history variable was estimated independent of each other owing to the fact that the variables measuring offense type were not independent (i.e. individuals could report more than one). Adjusted odds ratios (AOR) and 95% confidence intervals are reported. All analyses were conducted using the latent class functions in Stata version 15.1.

Results

Profile membership

A latent profile model consisting of six profiles was selected (see Table 1). Although AIC and BIC were slightly improved with a 7-profile solution, the profiles were not parsimonious and did not reach separation. That is, in the 7-profile model the profiles were not distinct in interpretation with overlap in defining features among three profiles specific to NMPO use. Specifically, while four of the profiles remained generally the same in the 6-profile and 7-profile models, two emerged with no defining characteristics. These two ambiguous profiles had similar rates of NMPO as another profile (the three profiles had NMPO use ranging 13–16 days). The two ambiguous profiles were not clearly separate on any substance other than marijuana, with mean days of use on all other substances in mid-range (6–16) providing no defining characteristics. Model ideals of homogeneity for latent techniques advise that well-fitting models have profiles that tend toward upper and lower bounds rather than middle scores, as an abundance of middle-range values creates issues with separation (i.e. the extent to which patterns vary across profiles and create distinct profiles). A six-profile model was the most parsimonious, homogenous, with separation. Random iterations and the log likelihood converged to the same six-factor model selected in 76.2% of tests indicating the six-profile solution was well-fitting and robust.

The six-profile model selected appears in Table 2, with mean number of days of substance use in the 30-days prior to incarceration reported. Profile 1 representing 9.4% of the sample was characterized by near daily alcohol use with substantial co-use of marijuana and NMPO about 50% of the month (Primarily Alcohol). Profile 2 was characterized by near-daily use of heroin and co-use of marijuana and NMPO about 40% of the month (Primarily Heroin). The most prevalent profile, with 34.3% of the sample, was characterized by Less PSU. While use of NMPO and marijuana was still substantial, compared to other profiles the Less PSU group did not have any drug use above 15 days per month. Profile 4, with 16.3% of the sample, was characterized by Tranquilizer PSU, with frequent use of NMPO and near daily use of tranquilizers. Co-use of marijuana and amphetamines was additionally high (Tranquilizer PSU), occurring 30–40% of the days of the month. Profile 5 was the smallest group with 7.8% of the sample. Individuals in this profile had daily use of buprenorphine with substantial co-use of marijuana, NMPO, and amphetamines about 40% of the month (Primarily Buprenorphine). Profile 6 was characterized by near daily cocaine use, high co-use of marijuana, NMPO, and heroin 50–60% of the month, and amphetamine use nearly 40% of the month (Stimulant-Opioid). Additional details of specific NMPOs, amphetamines, and tranquilizers used by each profile can be found in Supplementary Table S1.

Characteristics of sample

Full sociodemographic, physical health, mental health, and criminal history information of the total sample and by latent profile is provided in Table 3. The overall study population was predominantly white males in their 30 s with an average of 12 years of education/GED. The sample was equally split between rural and urban, with the majority (54%) employed prior to incarceration. Approximately one-third had experienced homelessness in the 12 months prior to incarceration and reported an average of two sources of financial strain. Twenty-one percent of the sample reported having HCV, and nearly 30% reported chronic pain. The average person had a history of 10 previous convictions. All sociodemographic variables were significantly different by latent profile as indicated by chi-square and ANOVA tests. Post-hoc Tukey-Kramer comparisons (p<.01) were performed after ANOVA results (results available upon request).

Multivariate models

Table 4 contains adjusted odds ratios and 95% confidence intervals predicting class membership. The Less PSU profile was chosen as the comparison group so that it could be understood how the higher risk profiles differed (i.e. which characteristics may be associated with riskier PSU patterns). This profile was also the most prevalent, which made it an ideal reference group. The AORs reported here are adjusted for all sociodemographic, physical, and mental health covariates as outlined in the analytic plan section. Criminal history variables were estimated independently of other criminal history variables.

Compared to Less PSU, individuals were more likely to be classified as Primarily Alcohol if they were older (AOR: 1.02, p<.05) and male (AOR: 1.76, p<.001). Individuals were less likely to be classified as Primarily Alcohol if they were unemployed prior to incarceration (AOR: 0.77, p<.05). Persons who reported using alcohol to cope (AOR: 27.68, p<.001) and with increasing number of convictions (AOR: 1.01, p<.001) were more likely to be represented by the Primarily Alcohol profile. Those who reported using prescription (AOR: 0.68, p<.001) or illegal drugs (AOR: 0.38, p<.001) to cope were less likely to be classified as Primarily Alcohol. Individuals were less likely to be identified by this profile if they had a 12-month history of arrests for drug crimes (AOR: 0.74, p<.01).

Compared with the Less PSU, individuals were more likely to be classified as Primarily Heroin if they were younger (AOR: 0.98, p<.01), had lived in urban area prior to their incarceration (rural AOR:0.24, p<.001), had increasing economic hardships (AOR:1.07, p<.001), or had a history of lifetime IDU (AOR:5.12, p<.001). Individuals who report using alcohol (AOR: 0.76, p<.05) or prescription drugs (AOR:0.73, p<.001) to cope were less likely, however to be identified by the Primarily Heroin profile. Increased likelihood of profile membership was found for those who reported use of illegal drugs to cope (AOR: 2.54, p<.001). Arrests for violent crimes (AOR:0.62, p<.01) or drug crimes (AOR:0.79, p<.05) were associated with decreased odds of being categorized as Primarily Heroin.

Individuals with lower levels of education (AOR:0.94, p<.001) or those who lived in a rural area prior to incarceration (AOR:1.27, p<.01) were more likely to be classified as Tranquilizer PSU as compared to Less PSU. Further, with a history of lifetime IDU (AOR:1.46, p<.001) and increased anxiety symptoms (AOR:1.04, p<.05) were also more likely to be classified by this profile's patterns. Reported use of alcohol (AOR:1.69, p<.001) and prescription drugs (AOR:2.90, p<.001) to cope, and increasing lifetime convictions (AOR:1.01, p<.001) increased the likelihood of being classified by Tranquilizer PSU patterns.

With Less PSU as the reference, individuals who were younger (AOR:0.98, p<.01), with lower levels of education (AOR:0.93, p<.01), male (AOR:1.56, p<.01), white (AOR:1.46, p<.001), or who lived in rural areas prior to incarceration (AOR:2.71, p<.001) were more likely to be in the Primarily Buprenorphine group. Individuals with increasing economic hardship (AOR: 1.05, p<.05) or lifetime IDU histories (AOR:2.06, p<.001) were more likely to be classified as Primarily Buprenorphine as well. Persons with increased anxiety symptoms (AOR:1.04, p<.05) or histories of using prescriptions to cope (AOR:1.79, p<.001) had increased odds of being in the Primarily Buprenorphine profile. Individuals were less likely to be in this profile with chronic pain (AOR: 0.77, p<.05), increased depression symptomology (AOR:0.96, p<.05) or with histories of arrests for drug crimes (AOR:0.56, p<.01).

Individuals who were male (AOR:1.41, p<.01), homeless before incarceration (AOR:1.42, p<.001), with lifetime IDU histories (AOR:1.53, p<.001), or HCV positive (AOR:1.31, p<.05) were most likely to be classified as Stimulant-Opioid. Individuals were also likely to be classified in Stimulant-Opioid with lower levels of education (AOR:0.94, p<.01), living in an urban county prior to their incarceration (rural AOR:0.61, p<.001), and increasing depression symptoms (AOR:1.05, p<.01). In contrast, persons with chronic pain were unlikely to be in this profile (AOR: 0.78, p<.05). Those who reported a history of using alcohol (AOR:2.92, p<.001) or illegal drugs (AOR:1.42, p<.01) to cope were significantly associated with the likelihood of being characterized by Stimulant Opioid patterns. Further a greater number of convictions (AOR:1.01, p<.001) and arrests for property crimes (AOR:1.45, p<.001) were associated with increased likelihood of being classified by Stimulant-Opioid profile as compared with Less PSU.

Risk factor variation among latent profiles

A qualitative summary of the latent profiles is provided in Table 5. These comparisons are supported by the multinomial logistic regression results, with secondary evidence derived from the bivariate associations. Three of the latent profiles were more likely to have comorbid mental health concerns: Tranquilizer PSU, Primarily Buprenorphine, and Stimulant-Opioid. The latter two profiles were most likely to report that they were HCV positive. While all profiles had risky PSU that could contribute to overdose, three profiles had heavy (40%+ of the month) co-use of substances known to contribute to overdose: Primarily Alcohol (co-use of NMPO and alcohol), Tranquilizer PSU (co-use of NMPO and tranquilizers), and Stimulant-Opioid (co-use of cocaine, heroin, and NMPO). While the exact timing of co-use of these substances is not known, the mean days of use indicate overlap of these high-risk combinations occurs 40% or more of the month. Additional considerations are provided in Table 5.

Discussion

The current research is among the first to explore PSU among a sample of justice-involved persons who use opioids. Specifically, LPA identified six distinct profiles of PSU involving opioids in the 30-days prior to incarceration with profiles distinguished by their use of Primarily Alcohol, Primarily Heroin, Less PSU, Tranquilizer PSU, Primarily Buprenorphine, and Stimulant-Opioid. These profiles differed in important ways which are relevant to public health and criminal justice systems and can be used to inform intervention development.

All profiles in the current research reported co-use of marijuana at least 40% of the month and did not distinguish the profiles. The high co-use of marijuana and opioids has been observed among PSU populations (Monga et al., 2007; Trenz et al., 2012; Wu et al., 2010). In a study of persons who use opioids in Canada, marijuana use was 50% or greater among latent classes (Monga et al., 2007). Previous research demonstrates the role of the endocannabinoid system in opioid use disorder, and the potential for marijuana to diminish opioid withdrawal (Bisaga et al., 2015). Considering all profiles reported substantial use of opioids by study design, it is possible that high marijuana use is related to a pharmacological desire or need to reduce symptoms of opioid withdrawal.

Another similarity among profiles was the role of substance use as a coping mechanism. Given the propensity for individuals in the five higher risk profiles examined to report using alcohol, prescription drugs, or illegal drugs as a method of coping, appropriate interventions that introduce effective coping mechanisms during incarceration are appropriate. Moreover, promoting effective coping mechanisms and addressing stressors prior to incarceration has significant potential to improve substance use outcomes. It has long been noted that relapse to substance use is likely during stressful experiences among individuals with limited coping skills (Rohsenow et al., 2001; Sinha, 2007). Providing coping skill training reduces future relapse, both when provided alone (Rohsenow et al., 2000, 2001) and in conjunction with pharmacotherapies (O'Malley et al., 1992). While therapeutic communities, a common prison-based substance program, often require desistance from unhealthy coping mechanisms, there is no known longitudinal research on the use of these coping skills post-release including the effects of skills training on post-release substance use. Research indicates individuals who enroll in therapeutic community aftercare are most likely to remain substance-free long-term (Inciardi et al., 2004), supporting the idea that assistance with coping skills in presence of relapse stimuli would be most effective (Rohsenow et al., 2001).

Of the six profiles, two have been similarly identified in studies of the general population (Fong et al., 2015; Harrell et al., 2012; Kuramoto et al., 2011; Patra et al., 2009; Wu et al., 2010), such that previous research has found a PSU class with comparably diverse PSU patterns similar to those of the Stimulant-Opioid and Tranquilizer PSU profiles. Among both profiles, individual's substance use was more diverse and severe (i.e. more days per month of use). Both profiles also had significant yet unique physical and mental health comorbidities (e.g. HCV positive, anxiety, depression) indicating acute needs as polysubstance diversity increases. Given that screening practices for physical and mental health in prisons and, more so, jails vary significantly (NCCHC, 2002), the information from brief substance use screeners could assist in linkage to appropriate preliminary services when other information is unavailable. Additionally, the use of stimulants with opioids is a more common PSU pattern, owing to more pleasurable effects or the use of stimulants to reduce opioid withdrawal symptoms (Leri et al., 2003). This repeated finding demonstrates that at the time of assessment, treatment providers have the potential to classify individuals PSU patterns. In the current 'fourth wave' of the opioid epidemic, when opioid-related harms due to the PSU of stimulants and opioids are on the rise (Kariisa et al., 2019) consideration of separate and unique treatment for this population is warranted. As research has indicated distinct motivations for stimulant-opioid co-use (e.g. euphoric effects, stave withdrawal), further understanding of the motivation of co-use among this population would be beneficial for intervention development.

Other targeted intervention should be considered specific to overdose risk. A study by Betts et al. (2016) found that individuals with certain PSU patterns were at increased risk of overdose only when psychological distress was also found. That is, something about the nature or way that distressed individuals consume multiple substances places them at increased risk for nonfatal overdose (Betts et al., 2016). The individuals categorized by the Tranquilizer PSU profile had comorbid mental health concerns and overlapping days of nonmedical use of tranquilizers (e.g. benzodiazepines) and opioid use two-thirds of the month. These individuals were also likely to have histories of lifetime IDU and be resource limited. Tailored interventions during incarceration that could be appropriate would include naloxone training, linkage to health care, and/or harm reduction training since these individuals are at extreme risk of negative outcomes without appropriate targeted interventions.

Overdose risk screening can be guided by understanding the PSU patterns of justice populations. All individuals in the current study face elevated risk of overdose following release (Binswanger et al., 2007), however the current research indicates there is a continuum of risk whereby certain individuals (e.g. Tranquilizer PSU, Stimulant-Opioids) are at greater risk owing to risky substance use combinations, comorbid mental and physical health concerns, and resource limitations (i.e. high economic hardship, previously homeless, rurally located). What may be appropriate follow-up from service providers following release may need to be adapted based on this continuum of risk. For example, ensuring mental health care services are available promptly and frequently post-release or addressing physical health concerns through settings such as specialized transitions clinics may be more urgent for certain populations, and knowledge of pre-incarceration PSU patterns could assist in post-release planning.

Findings also indicate that intervention by PSU pattern can be adapted specific to rural-urban locale. Consider individuals in the Primarily Buprenorphine group, who represent a unique profile which has not previously been found in the literature. The association of this profile with rurality is important to consider owing to limited resources in rural areas, including limited buprenorphine and other treatment access (Andrilla et al., 2019; Bunting et al., 2018). Appropriate linkage to services, including medications for opioid use disorder, during incarceration are critical and post-release planning specific to PSU patterns could be beneficial to reentry outcomes.

Limitations & recommendations for future research

This research was among the first to utilize LPA with 30-day indicators of substance use including opioids. The only other known study to explore PSU using continuous latent variable is Parsons and colleagues (Parsons et al., 2014), which was a limited sample of HIV positive adults over the age of 50 in New York City. Future research should consider continuous indicators and LPA so that more nuanced understandings of PSU may occur. Improved polysubstance use measures that capture route of administration, stratification by injection drug use, simultaneous and sequential use, as well as studies that explore motivations for PSU are needed.

Future studies should improve upon the limitations of the current research. This study explored PSU among a group of individuals enrolled in correctional treatment in the state of Kentucky in the United States. Certain patterns may be unique to the state. Further, individuals reported use of opioids and future research should consider patterns of substance use among larger substance use cohorts, not involving opioids. Additionally, not all individuals who use opioids were represented- as the treatment sample represents a population who were recommended to treatment by the parole board, or treatment seeking on their own behalf. Whenever available, associated variables measured the 30-days prior to incarceration so as to be consistent with the 30-day LPA indicators. However, this was not always possible, due to measurement design and leaves uncertain the causality of results. Finally, all behaviors were self-reported in a criminal justice setting upon entrance to treatment. While extensive research has indicated that self-report measures of substance use are likely legitimate (Darke, 1998; Denis et al., 2012), there is the possibility of inaccurate details due to lack of rapport, bias, or recall. Particularly relevant is the concern of recall for justice-involved populations. In programs such as the current one, data about substance use are not gathered until individuals enter the SAP. However, research has found that in general justice and other vulnerable populations have good recall of their behavior (Anglin et al., 1993; Darke, 1998; Napper et al., 2010). This recall may vary by substance (Napper et al., 2010) indicating that in general, recall of justice populations requires further study.

Conclusions

The current research is the first to examine the polysubstance profiles of justice-involved persons who use opioids. There were distinct profiles of polysubstance use involving opioids, highlighting the diverse substance involvement of justice-involved populations. The current sample differed in these patterns of use by sociodemographic, physical health, mental health, and criminal history. Justice involvement provides a crucial point for intervention and criminal justice agencies should consider treatment efforts focused on unique patterns of substance use. Tailoring intervention efforts during incarceration has the potential to reduce risky PSU patterns post-release, reduce future criminal justice involvement, and save lives through overdose risk assessment. Recognizing that opioid use, and substance use in general, is heterogenous and diverse is crucial to successful treatment and intervention success. Future research of the diverse substance patterns of justice-involved individuals, to include longitudinal research, is crucial to curbing the opioid epidemic.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

Fit statistics for a latent profile analysis of polysubstance use involving opioids.

Number of Profiles	Log-likelihood	Degrees of freedom	Akaike Information Criteria	Bayesian Information Criteria	Entropy	Likelihood ratio test (p-value)
1	−204822.7	16	409677.5	409786.1	1.00	NA
2	−201122.9	25	402295.7	402465.5	0.95	7384.27 (<0.001)
3	−200226.8	34	400521.7	400752.6	0.93	1790.28 (<0.001)
4	−199959.5	43	400005.1	400297.1	0.88	530.50 (<0.001)
5	−197275.0	52	394654.1	395007.2	0.86	5341.76 (<0.001)
6	**−196888.3**	**61**	**393898.7**	**394312.9**	**0.93**	**1250.72 (<0.001)**
7	−196519.7	70	393179.4	393654.7	0.85	241.70 (<0.001)

Note: Latent profile selected shown in bold.

Table 2.

Latent profile conditional means for polysubstance use involving opioids in the 30-days prior to incarceration.

Descriptive profile abbreviation	Profile 1 (N=618) Primarily Alcohol	Profile 2 (N=1,247) Primarily Heroin	Profile 3 (N=2,255) Less PSU	Profile 4 (N=1,070) Tranquilizer PSU	Profile 5 (N=513) Primarily Buprenorphine	Profile 6 (N=866) Stimulant-Opioid
Latent Profile indicators: Prior 30-day use						
Alcohol	28.03	3.94	2.43	7.51	1.96	10.22
Cocaine	1.28	1.73	0.73	1.20	0.82	27.38
Marijuana	14.65	11.53	12.11	16.47	12.18	17.99
Heroin	1.20	28.88	1.37	7.47	1.30	14.93
Buprenorphine	4.93	4.56	1.63	9.46	29.03	8.60
NMPO	14.30	12.94	14.21	20.80	12.28	18.18
Amphetamines	9.38	9.18	10.77	12.04	12.73	11.18
Tranquilizers	2.78	2.52	1.78	28.66	2.29	11.01
Profile Prevalence	9.41%	18.98%	34.33%	16.29%	7.81%	13.18%

Note: Shaded cells of substance use greater than 15 days per month to assist with interpretability.

NMPO = Nonmedical use of prescription opioids, PSU = polysubstance use.

Table 3.

Characteristics of justice-involved sample by most likely profile membership of polysubstance use patterns involving opioids ($N = 6{,}569$).

	Total Sample	Primarily Alcohol	Primarily Heroin	Less PSU	Tranquilizer PSU	Primarily Buprenorphine	Stimulant-Opioid
Sociodemographic							
Age	32.72 (8.07)	34.22 (8.88)	31.58 (7.17)	32.87 (8.24)	33.28 (8.47)	32.12 (7.27)	32.52 (7.89)
Education Level	11.91 (2.13)	11.88 (2.10)	12.02 (1.98)	12.02 (2.10)	11.77 (2.30)	11.63 (2.13)	11.80 (2.20)
Male	81.9	88.7	80.3	81.2	79.4	83.6	83.0
White	60.7	57.3	65.0	59.0	58.4	68.4	59.7
Rural	50.2	54.0	28.0	52.9	62.1	75.8	42.4
Unemployed	45.7	38.7	46.7	45.3	48.4	46.8	46.4
Homeless	28.0	27.7	36.1	23.5	23.5	23.0	36.7
Economic Hardship (R:0–8)	1.93 (2.48)	1.88 (2.45)	2.30 (2.69)	1.69 (2.29)	1.82 (2.37)	1.83 (2.39)	2.27 (2.71)
Lifetime injection drug use	65.7	49.8	84.3	56.5	67.1	73.7	67.9
Physical Health							
HCV positive	21.0	13.4	26.8	17.3	21.1	24.4	25.4
Chronic Pain	29.1	28.5	26.3	29.5	36.1	25.1	27.6
Number of poor physical health days in past month	7.23 (11.92)	6.14 (11.40)	7.73 (12.23)	6.37 (11.29)	9.05 (12.83)	6.26 (11.16)	7.85 (12.35)
Mental Health							
Anxiety (R:0–7)	3.48 (3.21)	3.52 (3.23)	3.48 (3.21)	3.13 (3.17)	3.96 (3.19)	3.34 (3.23)	3.90 (3.18)
Depression (R:0–9)	4.30 (3.62)	4.29 (3.65)	4.46 (3.63)	3.83 (3.60)	4.84 (3.59)	3.76 (3.60)	5.00 (3.46)
Number of poor mental health days in past month	11.74 (13.70)	11.91 (13.89)	11.99 (13.89)	10.53 (13.23)	13.95 (13.99)	10.24 (13.19)	12.59 (14.00)
Use alcohol to cope	27.5	67.0	19.1	17.9	31.8	15.2	38.2
Use Rx drugs to cope	50.7	48.9	42.8	43.4	73.0	55.0	52.0
Use illegal drugs to cope	71.7	64.4	80.1	63.7	80.6	66.1	78.3
Criminal History							
Lifetime number of convictions	10.10 (14.29)	11.48 (16.23)	10.07 (12.63)	8.69 (12.55)	11.07 (15.99)	9.20 (14.23)	12.19 (16.67)
Arrest for property crimes past 12-months[a]	18.4	17.3	20.4	16.2	17.0	18.5	23.9
Arrest for violent crimes past 12-months[b]	9.8	12.6	6.5	10.1	10.8	7.0	12.1
Arrest for drug crimes past 12-months[c]	29.0	23.1	28.7	31.7	29.0	26.7	28.1

Notes: PSU = polysubstance use; Percentages and means (SD) presented.

All variables significant at $p<.001$ level with exception of unemployment which is significant at the level of $p<.01$.

[a]Drug crimes included trafficking, possession, paraphernalia, and manufacturing charges.

[b]Violent crimes included weapon offenses, robbery, assault, rape, and homicide.

[c]Property crimes included shoplifting, burglary, and arson.

Table 4.

Estimated adjusted odds ratios and 95% confidence intervals between relevant variables and latent polysubstance use profiles compared to Less PSU profile ($N = 6{,}569$).

	Primarily Alcohol	Primarily Heroin	Tranquilizer PSU	Primarily Buprenorphine	Stimulant-Opioid
Sociodemographic					
Age	1.02 * (1.00–1.03)	0.98 ** (0.97–0.99)	1.00 (0.99–1.01)	0.98 ** (0.96–0.99)	1.00 (0.99–1.01)
Education Level	0.99 (0.94–1.03)	1.00 (0.96–1.03)	0.94 *** (0.91–0.98)	0.93 ** (0.89–0.98)	0.94 ** (0.91–0.98)
Male	1.76 *** (1.30–2.39)	1.22 (0.97–1.45)	1.14 (0.78–1.16)	1.56 ** (1.16–2.11)	1.41 ** (1.12–1.78)
White	0.82 (0.66–1.01)	1.13 (0.98–1.37)	0.91 (0.79–1.09)	1.46 *** (1.16–1.83)	0.89 (0.75–1.06)
Rural	0.85 (0.69–1.05)	0.24 *** (0.23–0.32)	1.27 ** (1.17–1.61)	2.71 *** (2.11–3.48)	0.61 *** (0.51–0.73)
Unemployed	0.77 * (0.63–0.96)	1.04 (0.87–1.17)	1.08 (0.94–1.29)	0.99 (0.79–1.23)	1.00 (0.84–1.18)
Homeless	1.24 (0.96–1.59)	1.17 (1.03–1.50)	0.83 (0.75–1.11)	0.93 (0.71–1.22)	1.42 *** (1.16–1.74)
Economic Hardship	1.01 (0.97–1.06)	1.07 *** (1.04–1.11)	0.99 (0.99–1.06)	1.05 * (1.00–1.10)	1.03 (1.00–1.07)
Injection drug use	1.11 (0.89–1.38)	5.12 *** (4.41–6.56)	1.46 *** (1.36–1.88)	2.06 *** (1.61–2.64)	1.53 *** (1.26–1.85)
Physical Health					
HCV positive	0.84 (0.63–1.13)	1.12 (0.98–1.44)	0.95 (0.84–1.27)	1.23 (0.95–1.61)	1.31 * (1.05–1.62)
Chronic Pain	0.80 (0.63–1.02)	0.84 (0.69–1.01)	1.08 (1.04–1.49)	0.77 (0.59–1.00)	0.78 * (0.63–0.95)
Number of poor physical health days in past month	1.00 (0.99–1.01)	1.00 (1.00–1.01)	1.01 (1.01–1.02)	1.00 (0.99–1.01)	1.00 (0.99–1.01)
Mental Health					
Anxiety	1.03 (0.99–1.08)	0.99 (0.95–1.03)	1.04 * (1.01–1.08)	1.04 * (1.00–1.09)	1.02 (0.99–1.06)
Depression	0.98 (0.95–1.02)	1.00 (0.96–1.05)	1.01 (0.98–1.06)	0.96 * (0.92–0.99)	1.05 ** (1.02–1.09)

	Primarily Alcohol	Primarily Heroin	Tranquilizer PSU	Primarily Buprenorphine	Stimulant-Opioid
Number of poor mental health days in past month	1.00 (0.99–1.01)	0.99 (0.99–1.00)	1.00 (1.00–1.01)	1.00 (0.99–1.01)	0.99 (0.99–1.00)
Use alcohol to cope	27.68*** (20.87–36.70)	0.76* (0.59–0.97)	1.69*** (1.36–2.03)	0.77 (0.69–1.17)	2.92*** (2.37–3.60)
Use Rx drugs to cope	0.68*** (0.53–0.87)	0.73*** (0.60–0.87)	2.90*** (2.39–3.55)	1.79*** (1.39–2.30)	0.88 (0.72–1.07)
Use illegal drugs to cope	0.38*** (0.29–0.51)	2.54*** (2.04–3.18)	1.15 (0.92–1.42)	0.90 (0.68–1.15)	1.42** (1.14–1.78)
Criminal History[a]					
Lifetime number of convictions	1.01*** (1.00–1.02)	1.01 (1.00–1.01)	1.01*** (1.01–1.02)	1.00 (1.00–1.01)	1.01*** (1.01–1.02)
Arrest for property crimes past 12-months	1.10 (0.76–1.31)	1.17 (0.94–1.45)	1.00 (0.81–1.24)	1.14 (0.87–1.50)	1.45*** (1.18–1.77)
Arrest for violent crimes past 12-months	1.07 (0.78–1.45)	0.62** (0.45–0.85)	1.12 (0.87–1.46)	0.56** (0.36–0.86)	1.15 (0.88–1.51)
Arrest for drug crimes past 12-months	0.74** (0.59–0.94)	0.79* (0.65–0.95)	0.89 (0.74–1.06)	0.80 (0.63–1.02)	0.82* (0.68–0.99)

Note: PSU = polysubstance use; Significance indicated by.

* p<.05,

** p<.01,

*** p<.001.

Models adjusted for all sociodemographic, mental, and physical health variables.

[a] Criminal history variables are modeled individually, adjusted for all variables.

Table 5.

Comparison of latent profiles considering known risk factors.

Risk Factor	Primarily Alcohol	Primarily Heroin	Less PSU	Tranquilizer PSU	Primarily Buprenorphine	Stimulant-Opioid
Comorbid mental health concerns				X	X	X
HCV positive		X				X
Heavy co-use of substances known to contribute to overdose	X			X		X
Homeless		X				X
History of injection drug use		X		X	X	X
Resource limited (high economic hardship and/or rurally located)		X		X	X	X
Concerns of tolerance (extensive criminal histories)	X					X

Note: PSU = polysubstance use. Categorizations made based on bivariate and multinomial logistic regression results. Results indicate other profiles are more at risk than the Less PSU profile, but this profile still represents a vulnerable population and risk is ever-present.