## ABSTRACT

JOHNSON, KIERSTEN L. A Latent Class Analysis of Concordance and Discordance between Results of Drug Use Assessments among Adults with Schizophrenia. (Under the direction of Dr. Sarah L. Desmarais).

Researchers and clinicians frequently conduct drug use assessments among adults with schizophrenia to identify drug users and inform treatment decisions. Results of multiple measures may be used in combination; however, there may be discordance between results. Furthermore, results may be affected by confounding variables unrelated to drug use, such as participant characteristics (e.g., age, sex, and race/ethnicity). In a large sample of adults with schizophrenia (*N*=1,460), I examined discordance between self-report, collateral report, clinician drug use ratings, hair radioimmunoassay (RIA), and drug urinalysis. I conducted latent class, bivariate, and multivariable analyses to: (a) identify classes of concordance/discordance; (b) examine distributions of participant age, sex, and race/ethnicity within classes; and (c) identify characteristics that differentiate participants across classes. Results of latent class analyses indicated that a four-class model best fit the data. Class 1 was comprised of participants with near-zero probabilities of being classified as using drugs by each of the five measures. Class 2 included participants for whom all measures indicated drug use over half of the time. Classes 3 and 4, in contrast, were discordant in nature. Class 3 was comprised of participants for whom biological tests and collateral report indicated non-use while self-report and clinician ratings indicated use. Class 4 included participants who were classified as non-users by all measures except for hair RIA. Bivariate and multivariable analyses indicated that participant age, sex, and race/ethnicity differed significantly across classes. Results showed that younger, male, and Black participants were more likely to be classified as drug users than drug non-users. Compared to those in Class 1, participants in

Class 3 were more likely to be younger in age, while participants in Class 4 were more likely to be Black than White. This study is the first application of latent class analysis to evaluate discordance between results of drug use assessment methods. Findings showed that discordance between results occurs at non-trivial rates and is, in part, attributable to participant age and race/ethnicity. These results may assist in developing population-specific guidelines to limit discordance, reduce false positives, and, ultimately, improve detection and treatment of drug use in adults with schizophrenia.

# A Latent Class Analysis of Concordance and Discordance between Results of Drug Use Assessments among Adults with Schizophrenia

by
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## BIOGRAPHY

Kiersten Laine Johnson was born on August 25th, 1989 in High Point, North Carolina. She grew up in nearby Greensboro, where she attended Western Guilford High School. After graduating with honors from the University of North Carolina at Chapel Hill in 2011, she entered the Psychology in the Public Interest program at North Carolina State University in 2012. Under the direction of Dr. Sarah Desmarais, her research interests include violence risk assessment and correlates of substance use, violence, and victimization in adults with mental illness. Kiersten lives in Raleigh with her husband, Brant, and golden retriever, Link.

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## Introduction and Purpose of Research

The co-occurrence of schizophrenia and illicit drug use is associated with serious adverse outcomes such as violence, homelessness, treatment noncompliance, and increased psychotic symptoms (Swanson et al., 2006; Reimherr, Swartz, & Olsen, 2010; Swofford, Scheller-Gilkey, Miller, Woolwine, & Mance, 2000). Accordingly, accurate identification of illicit drug use is critical for research and clinical practice with this population (Bennett, 2009; Carey & Correia, 1998; Drake, Osher, & Wallach, 1989). On an individual level, results of drug use assessments inform decisions regarding medication, treatment programs, and level of supervision (Center for Substance Abuse Treatment, 2005; 2009). More broadly, findings of these assessments contribute to estimates of drug use prevalence (Grant et al., 2006) and relevant policy formation (Regier et al., 1998). Considered the "gold standard", structured diagnostic approaches, such as the Structured Clinical Interview for DSM-IV (SCID; Spitzer, Williams, Gibbon, & First, 1996) and the Diagnostic Interview Schedule (Robins et al., 1988), are time intensive, costly, and require considerable training (Bennett, 2009; Desmarais, Van Dorn, Sellers, Young, & Swartz, 2013; Wolford et al., 1999). Consequently, a large number of screening methods have been developed; to demonstrate, the Alcohol & Drug Abuse Institute (2013) has record of 169 public screening tools intended for use with adults.

The core components of these numerous assessment options are by and large the same; frequently used measures include self-report, collateral report, clinician interviews, and biological tests, such as drug urinalysis, radioimmunoassay (RIA) of hair samples, and

blood tests. Such measures are increasingly used in combination by researchers and clinicians alike to improve identification of drug use among adults with mental illnesses. Though this multi-method approach may increase detection rates (Drake et al., 1990; Swartz, Swanson, & Hannon, 2003), it introduces the potential for discordance between test results. In other words, situations will arise in which one or more measures classify an individual as a drug user, while results of other tests indicate the opposite. For example, in a sample of adults with schizophrenia, including information from multiple measures led to over-identification of drug use compared to SCID diagnoses (Desmarais et al., 2013). Convention has been to classify an individual as drug using if at least one of the measures produces a positive result (Bahorik, Newhill, Queen, & Eack, 2013; Drake et al., 1990; Swartz et al., 2003). If the result is a false positive, however, doing so may have devastating consequences; for instance, it may result in the misallocation of limited treatment resources to non-users. Alternatively, it may preclude treatment and/or reduce housing options, as many programs require a period of abstinence prior to treatment and consider use grounds for dismissal (Brunette, Mueser, & Drake, 2004; Drake et al., 2001). Moreover, false positives may overestimate the prevalence of drug use in epidemiological research and misinform related policies.

Given these potential consequences of incorrect classification, research has explored factors that may affect assessment results. Findings of this work suggest differences in the reliability and validity of drug use measures as a function of participant age, sex, and race/ethnicity (Bennett, 2009). To demonstrate, in a study evaluating self-report of substance

use in homeless adults (percentage with schizophrenia unspecified), better reliability was associated with both younger and female participants (Drake, McHugo, & Biesanz, 1995). Another, more recent study found older adults with schizophrenia to be more likely than their younger counterparts to conceal their drug use in self-report (Bahorik et al., 2013, but see Van Dorn, Desmarais, Swartz, Young, & Sellers, 2014). Racial differences in self-report have also been noted, with research suggesting that Black respondents may be less likely to disclose drug use (Fendrich, Johnson, Wislar, Hubbell, & Spiehler, 2004; Ledgerwood, Goldberger, Risk, Lewis, & Kato Price, 2008). Additionally, a number of general population studies have examined a potential racial bias in biological tests, with mixed results: some cite an over-identification of drug use due to metabolites in African American hair (Borges, Roberts, Wilkins, & Rollins, 2003; Cone & Joseph, 1996; Ledgerwood et al., 2008), whereas others find no racial disparity (Hoffman, 1999; Kelly, Mieczkowski, & Sweeney, 2000; Mieczkowski, 2011). Finally, a study of adults with schizophrenia found that inclusion of biological tests as part of a multi-method assessment approach improved accuracy for White participants but not for their Black counterparts (Van Dorn, Desmarais, Young, Sellers, & Swartz, 2012).

All told, there is some evidence that discordance among drug test results reflects factors beyond use itself (Bennett, 2009). If indeed this is the case, there are direct implications for policy and practice. Specifically, rather than simply implementing the ‘most reliable’ measure or set of measures overall, researchers and clinicians should consider the “menu of assessment techniques” available, including their strengths as well as potential

biases, to match strategies to each individual (Bennett, 2009, p. 61). For example, if there is support for an over-identification of drug use in hair RIA of Black individuals, then this approach should not be used, or at least, results should be interpreted with caution (Cone & Joseph, 1996). However, there is a need for further research systematically evaluating the potential associations of participant characteristics with discordance between drug test results in adults with schizophrenia.

## Purpose of Research

To date, no studies have applied latent class analysis (LCA) to evaluate drug use measures in adults with schizophrenia, despite it being recognized as a state-of-the-art analytic approach (Vermunt & Magidson, 2004). This statistical technique reduces the number of cases based on similar response patterns, resulting in a smaller set of class memberships (Hagenaars & McCutcheon, 2002). Thus, LCA can be used to identify discrete subgroups based upon categorical or continuous observed variables (Vermunt & Magidson, 2004) and to more fully explain the relationship between observed variables. The development of more sophisticated statistical methods, coupled with the introduction of more general latent class models in the late 1970s, made feasible the application of LCA. Today, LCA represents one of the fastest growing areas in the field of applied statistics (Hagenaars & McCutcheon, 2002). Accordingly, the two aims of this project are:

1. To identify latent classes of concordance/discordance between self-report, collateral report, clinician interviews, and biological tests.
2. To examine participant age, sex, and race/ethnicity as correlates of these classes.

# Literature Review

## Co-occurrence of Schizophrenia and Drug Use

Illicit drug use occurs at high rates in adults with schizophrenia: over a quarter of adults with schizophrenia are diagnosed with a drug use disorder in their lifetime (Regier et al., 1990; Vincenti et al., 2010), with similar rates for current disorders (Fowler, Carr, Carter, & Lewin, 1998) and even higher rates of use (Swartz et al., 2006a). Estimates suggest the lifetime risk of developing a drug use disorder is up to six times greater for adults with schizophrenia than for the general population (Regier et al., 1990). This heightened risk of drug use has been attributed to a variety of factors, including social networks, quality of living environment, poverty, coping, interpersonal skills and social functioning (Gregg, Barrowclough, & Haddock, 2007). Consequently, researchers and clinicians who work with adults with schizophrenia regularly face issues associated with drug use.

Some experts suggest that adults with mental illnesses – schizophrenia or otherwise – are more vulnerable to the negative effects of drug use that adults without mental illnesses, such that any use, whether disordered or not, leads to impaired functioning. Specifically, the supersensitivity hypothesis suggests that adults with mental illnesses have a psychobiological vulnerability, determined by genetic and early environmental events, that is responsible for triggering onset or relapses of a psychiatric disorder. Whereas psychotropic medications serve to decrease this vulnerability, alcohol and/or drug use may increase it. As a result, adults with mental illnesses may be more likely than the general population to experience adverse consequences from substance use (Mueser, Drake, & Wallach, 1998). Furthermore,

these negative outcomes may result from lower levels of use than those seen in the general population (Drake et al., 1989; Drake & Wallach, 1993). To demonstrate, several studies have shown participants with schizophrenia react strongly to small doses of amphetamine that generate minimal responses in participants without a mental illness (Janowsky & Davis, 1976; Janowsky, El-Yousef, Davis, & Sekerke, 1973; Lieberman, Kane, & Alvir, 1987; Lieberman et al., 1984).

Indeed, drug use by adults with schizophrenia – whether it meets the diagnostic criteria for disordered use or not – has been strongly linked to a number of negative outcomes in the research literature. For example, prior research has shown that drug users are significantly more likely to be homeless than non-users (Gelberg, Linn, & Leake, 1988; Reimherr et al., 2010). There is also evidence of a significant association between drug use and treatment noncompliance: in a study with schizophrenic patients ($n$ = 37), drug users experienced four times as many psychiatric relapses as non-users due to treatment noncompliance over the year-long course of the study (Swofford, Kasckow, Scheller-Gilkey, & Inderbitzen, 1996). Additionally, the co-occurrence of schizophrenia and drug use is associated with an increased number of psychotic symptoms and psychiatric relapses (Dixon, 1999; Pencer & Addington, 2003; Swofford et al., 2000), which, in turn, increase risk for other adverse outcomes (Swanson et al., 2006; Swartz et al., 1998; Van Dorn, Volavka, & Johnson, 2012).

The hazards associated with drug use by adults with schizophrenia also have implications for public policy and public safety. Events precipitated by drug use, such as

treatment noncompliance and psychiatric decompensation, can necessitate hospitalization and crisis-oriented care; estimates suggest the cost of care associated with schizophrenic patients with co-occurring substance disorders to be over $10,000 greater annually than for their non-substance using counterparts (Dickey & Azeni, 1996). Moreover, drug use has been associated with a 2.5-factor increase in the perpetration of serious violent behavior in adults with schizophrenia (Swanson et al., 2006). Though many effective approaches exist for integrating the treatment of mental health and drug use problems, they necessitate *accurate* identification of drug use (Drake et al., 2001; Drake, Mueser, Brunette, & McHugo, 2004).

**Drug Use Assessment Approaches**

Past studies on the accuracy of different drug use assessment methods have generally taken on one of two strategies. The first strategy involves evaluating the results of each measure separately in an attempt to identify the 'most accurate' approach. The second strategy involves examining accuracy when the results of multiple measures are combined. Findings of studies implementing the first strategy have typically found adequate accuracy across measures (Bryant, Rounsaville, Spitzer, & Williams, 1992; Desmarais et al., 2013; Van Dorn, Desmarais, et al., 2012). However, others have cast doubts on whether assessments geared for the general population perform adequately in adults with serious mental illnesses, including schizophrenia, schizoaffective disorder, bipolar disorder, and major depression. For example, Wolford and colleagues (1999) examined the classification accuracy of self-report, medical exams, drug urinalysis, and collateral report by a family member, friend, or caregiver in a sample of 320 patients recently admitted to a psychiatric

hospital. The majority of participants were female (53.4%), White (97.8%), and had a primary diagnosis of schizophrenia (29.4%). The criterion was the combined results of the SCID and AUS/DUS assessments; a positive rating on either measure indicated drug use. Bivariate analyses showed no significant relationships between the criterion measures and results of medical exams or biological tests. In contrast, participant self-report and collateral report both discriminated between users and non-users (*p*s < .001). The authors concluded that many of the drug use measures employed in the general population may have "limited utility" in adults with serious mental illnesses (p. 324).

Studies examining drug use assessment accuracy when results of multiple tests are combined (i.e., the second strategy) have produced more favorable findings overall. For example, Drake and colleagues (1990) looked at the consensus diagnoses (determined by combining information from clinical records, clinician ratings, and self-report) in a rural sample of 75 outpatients with schizophrenia or schizoaffective disorder. The majority of participants were female (52.0%), with a primary diagnosis of schizophrenia (89.3%). There were multiple cases in which the results of the drug use measures were discordant, both for current ($n$ = 6) and lifetime drug use ($n$ = 11); these cases ultimately were classified as using. Data analysis used Kendall's tau coefficient to examine the association between results of the different assessment approaches. The criterion was a DSM-III-R (American Psychiatric Association, 1987) classification of drug use or dependence. Results indicated that consensus diagnoses were positively associated with the DSM-III-R classifications ($p$ < .001). Despite its relatively small sample size, this study has been used to justify the adoption of multi-

method assessment approaches with adults with schizophrenia (see Desmarais et al., 2013 for further review).

Mentioned earlier, two recent evaluations of the data included herein have examined results of both single and multi-measure drug use assessment approaches within the same sample. Desmarais and colleagues (2013) examined clinician ratings on the AUS/DUS, self-report, collateral report, drug urinalysis and RIA of hair samples to identify drug use using baseline data drawn from the National Institute of Mental Health (NIMH) Clinical Antipsychotic Trials of Intervention Effectiveness (CATIE) study (Lieberman et al., 2005). Briefly, the CATIE study examined antipsychotic medication effectiveness for adults with schizophrenia ($N$ = 1,460); its methodology is described more fully below (see Research Design). Results of SCID for the DSM-III-R (First, Spitzer, Gibbon, & Williams, 1996) assessments served as the criterion measure. Calculations of sensitivity, specificity, positive predictive values, negative predictive values, percent classified correctly, and the Areas under the Curve (AUC) of Receiver Operating Characteristic curves, indicated that assessment accuracy was good and comparable across measures. Regression analyses were conducted to see if multi-method assessments improved classification accuracy. Results showed that biological tests and clinician ratings added minimal accuracy over self-report alone; specifically, though model fit increased in each step ($\Delta\chi^2 = 26.15$, $p < .001$ and $\Delta\chi^2 = 10.83$, $p < .001$, respectively), biological tests increased $R^2$ by just .05 and clinician ratings, .01.

Van Dorn, Desmarais, and colleagues (2012) evaluated self-report and biological tests for assessing illicit drug use in the same CATIE study baseline data. Results of SCID for the DSM-III-R assessments and self-reported drug use in the past three months were used as criterion measures. After conducting sensitivity, specificity, and conditional probabilities as well as AUCs for each measure, results illustrated good accuracy across tests. Hierarchical logistic regression analyses examined the incremental validity of biological tests over self-report alone in order to identify factors affecting accuracy. Results showed that assessment accuracy improved with the addition of biological tests for White participants ($R^2 = 0.08$, $\Delta\chi^2 = 10.14$, $p < .01$) but not for Black participants ($R^2 = 0.03$, $\Delta\chi^2 = 5.09$, $p > .05$), providing further evidence of racial bias in hair testing.

In sum, results of prior research generally demonstrate accuracy of different drug use assessment approaches, though there are some differences in performance by measure and by participant characteristics. Thus, results of these screening approaches may be useful for estimating drug use prevalence, informing placements, and establishing treatment plans (Bennett, 2009). Though combining results of multiple assessment measures may increase rates of detection (e.g., Drake et al., 1990; see also Swartz et al., 2003), this practice also may introduce discordance between test results. Past studies have employed a conservative decision rule, classifying discordant cases as drug use (Bahorik et al., 2013; Drake et al., 1990; Swartz et al., 2003). While this strategy decreases likelihood of false negatives (i.e., failure to correctly identify a drug user), it also may increase likelihood of false positives (i.e., incorrect identification of a non-drug user as using), which are no less consequential.

Therefore, there is need for further research examining discordance between results of different drug use assessment approaches in adults with schizophrenia. In this study, I employed a state-of-the-art analytic strategy, LCA, to identify classes of concordance and discordance between drug use assessment results in a large sample of adults with schizophrenia. Specifically, I examined concordance and discordance between results of self-report, collateral report, clinician ratings on the DUS, RIA of hair samples, and drug urinalysis in detecting use of marijuana, cocaine, opiates, phencyclidine (PCP), amphetamines, and other illicit drugs. (Alcohol is excluded from analyses because the CATIE study did not include biological tests for alcohol use.) After identifying latent classes, I conducted bivariate and multivariable analyses to examine distributions of participant characteristics and identify their associations with class membership. This study represents the first application of LCA to evaluate discordance between results of different drug use assessment approaches in adults with schizophrenia, and advances our understanding of drug use assessment in this population.

## Methodology

### Research Design

I analyzed data from a large, secondary dataset in a psychometric design. The CATIE study is a double-blind, randomized clinical trial that examined antipsychotic medication effectiveness for adults with schizophrenia (Lieberman et al., 2005). The CATIE data are ideal for addressing the study aims for two reasons. First, the sample is sufficiently large and representative of the target population (Stroup et al., 2003). Second, the reliability and

validity of results from its drug use measures have previously been established (Desmarais et al., 2013; Van Dorn, Desmarais, et al., 2012). The present study examined results of drug use measures (i.e., self-report, collateral report, clinician rating, hair RIA, and drug urinalysis) administered at baseline as independent variables, with concordance/discordance between tests as the outcome of interest.

**Setting**

The CATIE study was conducted between January 2001 and December 2004 at 57 sites across the United States (16 university clinics, 10 state mental health agencies, seven Veterans' Affairs Medical Centers, six private non-profit centers, four private practice sites, and 14 mixed-system sites). Data from one site ($n$ = 33) were excluded due to concerns regarding data integrity. These sites systematically screened new or existing inpatients and outpatients with chronic or recurrent schizophrenia. Inclusion criteria were: (a) 18 years of age or older; (b) schizophrenia; and (c) ability to take oral antipsychotics. First episode and treatment-refractory patients were excluded. There were few other exclusion criteria; only 7% of screened patients were excluded from the study. (For further details regarding recruitment, as well as inclusion and exclusion criteria, see Stroup et al., 2003). The protocol was approved by local IRBs, and participants provided written informed consent. The RTI International and North Carolina State University IRBs approved the current study procedures.

## Participants

The present data are taken from baseline assessments (i.e., prior to randomization and initiation of experimental treatments) of 1,460 adults with schizophrenia enrolled in the CATIE study. Over half of participants were male (73.9%, *n* = 1,079), with 49.5% of participants identifying as White (*n* = 722), 34.7% (*n* = 506) Black, 11.6% (*n* = 106) Hispanic, and 4.2% (*n* = 61) "other/mixed" race. Age at baseline ranged between 18 and 67 years (*M* = 40.56, *SD* = 11.10). Detailed descriptions of the sample characteristics are available elsewhere (Keefe et al., 2006; Swartz et al., 2006a). Due to its broad inclusion criteria, the CATIE study sample is representative of its intended population of community-based adults with schizophrenia: enrolled participants included a wide range of schizophrenic patients, from partially remitted outpatients to exacerbated inpatients. Prior research illustrates that the CATIE sample resembles a usual-care, quasi-random, observational, and non-interventional population in its demographic and clinical characteristics (Swanson et al., 2006).

## Measures

Table 1 provides an overview of the variables included in the present analyses. They are described in detail below.

### Covariates

**Sex.** Participant sex is a dichotomous variable with 1 representing *female* and 0 representing *male*.

**Age.** The variable age is a continuous measure of participant age (in years) at the time of the baseline assessment.

**Race/ethnicity.** Respondent race/ethnicity is indicated by four variables: White, Black, Hispanic, and other race/ethnicity. Each variable is dichotomous, with 1 representing *group membership* and 0 representing *non-membership*.

**Drug Use Measures**

Drug use assessment measures were either administered to participants on the same day or on two consecutive days (M. Swartz, personal communication, August 22, 2013).[1] All measures tested for use of marijuana, cocaine, opiates, PCP, amphetamines, or other illicit drugs. These measures are described in greater detail below.

**Self-report.** Study participants reported their drug use in the prior three months in research interviews (see Appendix A). Items included use of each drug (i.e., marijuana, cocaine, opiates, PCP, amphetamines, or other). Participants indicated "yes" (1) or "no" (0) for each item. A positive response to one or more questions indicated *drug use*.

**Collateral report.** Interviews with family members/caregivers were conducted for 645 (44.2%) participants. Respondents rated the participant's excessive use of drugs in the prior month. Ratings (0 = never, 1 = rarely, 2 = occasionally, 3 = often) were recoded to indicate *use* (1), *abuse* (2), or *dependence* (3) (Swartz et al., 2006b). For the purposes of the present study, ratings of 1 or higher indicate *drug use*.

[1] While measures were administered at the same time, some cover different time frames; as a result, discordance may, in fact, reflect accurate results on the various tests.

**Clinician Drug Use Scale.** Medical doctors or experienced clinicians completed DUS (Drake et al., 1990) ratings for all participants (see Appendix B). Clinicians provided separate ratings (1 = abstinent, 2 = use without impairment, 3 = abuse, 4 = dependence, and 5 = dependence with institutionalization) regarding the participant's use of drugs over the prior three months by weighting evidence from self-report, interviews, behavioral observations, and collateral (e.g., family, community, day center, etc.). Results of SCID assessments and biological tests were not available to clinicians. CATIE study clinicians were trained using an approach that has been shown to minimize assessment error and increase reliability and validity in large multisite trials (Tracy, Adler, Rotrosen, Edson, & Lavori, 1997; Müller & Wetzel, 1998; Salyers & Mueser, 2001). Interrater reliability data are not available; however, prior studies using similar training protocols have found good interrater agreement (e.g., $\kappa$ = .95 for drug use, Drake et al., 1989). Resulting clinician ratings (1 = abstinent, 2 = use without impairment, 3 = abuse, 4 = dependence, and 5 = dependence with institutionalization) were recoded for analyses as *abstinence* (1), *use* (2), *abuse* (3), and *dependence* (4 or 5). For the purposes of the current study, ratings of 2 or higher indicate *drug use*, and were then recoded to *non-use* (0) and *use* (1).

**Hair assay.** Participant hair specimens were collected and analyzed by RIA, which assays drugs and their metabolites transferred from capillary circulation through the hair follicle to the internal structure of the hair (Baumgartner, Hill, & Bland, 1989). A tuft of hair about the diameter of pencil lead was cut from the back of the scalp. A larger volume was removed from participants with short hair. If none was present on the head, hair was taken

from the chest, arm, or leg. Samples 1.5 in. long were taken, affording assessment of drug use in the preceding three months. All hair samples were collected by study sites and sent to PsycheMedics Corporation for analysis. Values more than three standard deviations from the mean were then considered positive, indicating *drug use,* once confirmed by gas chromatography/mass spectrometry.

**Drug urinalysis.** Drug urinalysis was performed with a rapid multiple immunoassay urine drug test. Results were analyzed at Quintiles Laboratories. Generally, urine samples have a shorter window of drug detection than do RIA of hair samples, with an average detection window of one to four days (DuPont & Baumgartner, 1995; Verstraete, 2004). However, this time frame can vary by drug and frequency of use, with extremely chronic cocaine and marijuana use being detected up to three weeks after most recent use (Verstraete, 2004). Positive test results indicate *drug use*; however, positive test results due to use of prescribed medications on either hair RIA or drug urinalysis were not coded as positive.

## Statistical Analyses

This study employed latent class, bivariate, and multivariable analyses to: (a) identify classes of concordance/discordance between drug use measures; (b) examine distributions of participant age, sex, and race/ethnicity within classes; and (c) identify characteristics that differentiate participants across classes. Below, I describe each analytic strategy in further detail.

**Latent Class Analyses**

Latent class analyses (LCA) were conducted in Mplus 7.11 (Muthén & Muthén, 1998-2012) to identify concordant/discordant classes of drug use measures. Specifically, the drug use measures were entered into a latent class model with drug use (yes, no) as the outcome variable. Because collateral reports were completed for 44.2% of the sample, the LCA was first run with collateral reports included, and then excluded. Results were compared for consistency. Currently, there is no formal approach dictating appropriate sample size for LCA. However, conservative recommendations for factor analysis consider a sample size greater than 1,000 to be excellent (Comrey & Lee, 1992), an estimate which has been extended to LCA (Nylund, Asparouhov, & Muthén, 2007). As a result, the total sample size of 1,460 was sufficient for identifying latent classes.

There is no one commonly accepted approach for determining the number of classes in applications of LCA; likelihood-based tests (e.g., Lo–Mendell–Rubin, bootstrap likelihood ratio test) and information criterion tests (e.g., Bayesian information criterion, Akaike's information criterion) are used interchangeably. For my analyses, I used the bootstrap likelihood ratio test (BLRT), which has been demonstrated as the most consistent indicator across both likelihood-based and information criterion tests (Nylund et al., 2007). This method uses bootstrap samples to estimate the log likelihood difference distribution and obtain a *p* value to compare the increase in model fit between $k - 1$ and $k$ class models. Specifically, I: (1) estimated $k - 1$ and $k$ class models for calculating the -2* log likelihood difference; (2) generated a bootstrap sample under the $k - 1$ class model and computed the -

2* log likelihood difference between the two models; (3) repeated this process independently several times to approximate the true log likelihood difference distribution; (4) obtained the *p* value by comparing the distribution from (3) with the -2* log likelihood difference from (1); and (5) used the *p* value to determine if the $k - 1$ class model should be replaced by the *k* class model.

**Bivariate Analyses**

Once classes of concordance/discordance were identified, I conducted bivariate analyses to examine differences in age, sex, and race/ethnicity between classes in SPSS, v.19. A one-way ANOVA was conducted for age, with *post hoc* pairwise comparisons using Bonferroni adjusted *t*-tests. Chi-square tests were conducted for categorical variables (sex and race/ethnicity), with *post hoc* pairwise comparisons using Bonferroni adjusted *z*-tests. These analyses identify differences in the distribution of demographic characteristics between classes. Based on total sample size of 1,460 and as many as eight classes, I had power of approximately .89 to detect differences small in size (w = .10) for the chi-square analyses, and approximately .81 for the one-way ANOVA, calculated using G*Power 3.1.4 (Faul, Erdfelder, Lang, & Buchner, 2007).

**Multivariable Analyses**

I then conducted multinomial logistic regression in SPSS, v.19. For this statistical test, one level of the outcome is considered a reference category to which the other levels are compared (Tabachnick & Fidell, 2001). As a result, I obtained the probability that a participant belongs to a particular category; thus, in the present study, results indicate the

extent to which a participant characteristic (e.g., age, sex, and race/ethnicity) is associated with each concordant/discordant class. Odds ratios show the probability of membership in each class as compared to the designated reference group. For class membership, the reference group (i.e., concordant drug non-use) was selected from the classes identified through LCA. For the covariates of sex and race/ethnicity, female and White participants, respectively, served as reference groups. Based on total sample size of 1,460, I had power ranging from .75 to .83 to detect small effect sizes (w = .10) with up to eight classes, calculated using G*Power 3.1.4 (Faul et al., 2007).

**Missing Data**

Missing data in the CATIE has previously been classified as missing at random (MAR) due to the large amount of patient information collected (Shortreed & Moodie, 2012; Van Dorn et al., 2013). MAR indicates that the missingness may be a function of observed covariates and outcomes but is not related to the variable that has the missing data. Mplus provides maximum likelihood estimates when programmed to assume that data are MAR. Maximum likelihood is considered superior to multiple imputation due to its efficiency, consistency, and avoidance of imputation and analysis model conflict (Allison, 2012). Maximum likelihood first constructs a likelihood function and then creates parameter estimates that maximize the probability of observing what has been observed elsewhere in the model (Allison, 2012). For the multivariable analyses, there was no missing data in the independent (i.e., age, sex, race/ethnicity; Shortreed, Laber, Stroup, Pineau, & Murphy, under review) or dependent variables (i.e., classes).

# Results

## Latent Class Analyses

**Collateral reports included.** Both the Bayesian information criterion (BIC) and bootstrap likelihood ratio tests identified a four-class model as best fitting the data (sample-size adjusted BICs: three classes = 4371.41, four classes = 4353.48, five classes = 4372.36). The conditional probabilities, which illustrate the probability of each measure indicating drug use, are plotted for each of the four latent classes in Figure 1. Class 1 included participants with near-zero probabilities of being classified as drug user by each of the five measures. Class 2 included participants for whom all measures indicated drug use over half of the time. Class 3 was discordant in nature; whereas participants had near-zero probabilities of being classified as drug users by drug urinalysis, hair RIA, and collateral report, those same individuals were almost always identified as drug users by self-report ($p$ = .913) and clinician DUS ($p$ = .924). Class 4 was also discordant; here, participants were unlikely to be classified as drug users by all measures except hair RIA, which always classified them as drug users.

Participants were assigned to classes as indicated by posterior membership probabilities, which speak to the level of certainty in its categorizations. To demonstrate, a participant with a probability of .88 of belonging to Class 1, a .12 probability of belonging to Class 4, and a zero probability of belonging to Classes 2 or 3 would be assigned to Class 1. All four latent classes exhibited high posterior probabilities, indicating that the majority of participants were assigned to the correct class with very few cases of ambiguity in membership (Class 1: $M$ = .96, $SD$ = .08; Class 2: $M$ = .92, $SD$ = .15; Class 3: $M$ = .82, $SD$ =

.12; Class 4: *M* = .99, *SD* = .04). Descriptive analyses of the latent classes illustrated that Class 1 consisted of the majority of the sample (66.2%), followed by Class 2 (18.6%), Class 4 (10.1%), and Class 3 (5.2%).

**Collateral reports excluded.** When collateral reports were excluded from the latent class model, BIC and bootstrap likelihood ratio tests pointed to a four-class model (sample-size adjusted BICs: three classes = 3993.37, four classes = 3984.03, five classes = 4004.56). The model's conditional probabilities are plotted in Figure 2. Results were highly similar to those observed when collateral reports were included. Specifically, Class 1 had participants with near-zero probabilities of being classified as drug users by the four measures. Class 2 had participants for whom each measure indicated drug use over half of the time. Class 3 was discordant, including participants with low probabilities of being classified as drug users by drug urinalysis and hair RIA, but high probabilities by self-report and clinician DUS. Class 4 was also discordant; participants were unlikely to be classified as drug users by drug urinalysis, self-report, and clinician DUS, but highly likely to be classified as such by hair RIA. The four latent classes demonstrated high posterior probabilities (Class 1: *M* = .95, *SD* = .07; Class 2: *M* = .94, *SD* = .09; Class 3: *M* = .88, *SD* = .20; Class 4: *M* = .84, *SD* = .12). The majority of the sample was classified as Class 1 (65.7%), followed by Class 2 (14.9%), Class 4 (10.8%), and Class 3 (8.6%). Of note, the recommended class memberships derived by from the LCAs including and excluding collateral reports correlated highly, $r(1,458) = .995$, $p < .001$, with agreement observed in 95.8% of all cases.

## Descriptive Statistics

Tables 2 and 3 present demographic characteristics overall and within the four classes when collateral reports were included and excluded, respectively.

## Bivariate Analyses

**Collateral reports included.** Bivariate analyses showed the distribution of age, sex, and race/ethnicity differed significantly between classes when collateral reports were included (see Table 2, right hand column). Specifically, *post hoc* comparisons indicated that participants grouped in Classes 2 and 3 were significantly younger than those in Classes 1 and 4. Class 1 had a greater proportion of women than men, whereas the opposite was true in Class 2. Black participants were less likely to be in Class 1 compared to White and Hispanic participants. Conversely, Black participants were more likely to be in Class 2 than White and Hispanic participants. Black participants were also more likely to be categorized in Class 4 than their White counterparts. There were no significant differences in the proportion of Black, White and Hispanic participants in Class 3.

**Collateral reports excluded.** As above, bivariate analyses indicated that the distribution of age, sex, and race/ethnicity differed significantly between classes when collateral reports were excluded (see Table 3, right hand column). Specifically, *post hoc* comparisons revealed an identical pattern of results to those reported above, with one exception: Black participants were more likely to be in Class 2 than their White, but not Hispanic, counterparts.

**Multivariable Analyses**

**Collateral reports included.** Table 4 presents the results of the first multinomial logistic regression, including collateral report as a measure of drug use. Overall, there was moderate discrimination among categories on the basis of participant age, sex, and race/ethnicity, -2 LL = 1,239.89, $\chi^2$ (15) = 164.62, $p < .001$, Nagelkerke $R^2 = .13$. In the sections that follow, I describe factors associated with membership in Classes 2, 3 and 4, in relation to Class 1.

***Class 2.*** All three variables – age, sex, and race/ethnicity – significantly distinguished members of Class 2 from those of Class 1 (see Table 4). Younger participants were more likely to be grouped in Class 2 than Class 1. Male and Black participants were nearly three times as likely as female and White participants, respectively, to have measures agree on drug use rather than non-use.

***Class 3.*** Only participant age differentiated between Class 3 and Class 1, with younger participants significantly more likely to be grouped in Class 3 (see Table 4). Sex and race/ethnicity did not distinguish members of Class 3 from those of Class 1 ($p = .751$ and $ps \geq .134$, respectively).

***Class 4.*** Participant race/ethnicity distinguished members of Class 4 from those of Class 1 (see Table 4). Specifically, Black participants were over three times as likely as White participants to have the hair RIA measure indicate drug use while all other measures indicated non-use. Age and sex did not distinguish members of Class 4 from those of Class 1 ($p = .634$ and .415, respectively).

**Collateral reports excluded.** Table 5 presents the results of the second multinomial logistic regression, which excluded collateral report as a measure of drug use. Again, there was moderate discrimination among categories on the basis of participant age, sex, and race/ethnicity, -2 LL = 1,297.49, $\chi^2$ (15) = 159.87, $p < .001$, Nagelkerke $R^2 = .12$.

***Class 2.*** As was the case when collateral reports were included, age, sex, and race/ethnicity significantly distinguished members of Class 2 from those of Class 1 (see Table 5). Younger participants were more likely to have measures agree on drug use rather than non-use. Male and Black participants were nearly three times as likely as female and White participants, respectively, to be in Class 2 than Class 1.

***Class 3.*** Participant age and sex, but not race/ethnicity, differentiated between Class 3 and Class 1 (see Table 5). Younger participants were significantly more likely to be implicated as drug users by self-report and clinician DUS, while results of drug urinalysis and hair RIA indicate non-use. Likewise, male participants were 1.6 times more likely than female participants to be in Class 3 rather than Class 1. Participant race/ethnicity did not differentiate Class 3 from Class 1 ($ps \geq .084$).

***Class 4.*** Again, participant race/ethnicity was the sole difference between participants in Class 4 and Class 1. Specifically, Black participants were over three times as likely as White participants to have the hair RIA measure indicate drug use while all other measures indicated non-use. Age and sex did not distinguish members of Class 4 from those of Class 1 ($p = .474$ and .407, respectively).

# Discussion

Accurate identification of illicit drug use among adults with schizophrenia is critical for research, policy, and practice (Bennett, 2009; Carey & Correia, 1998; Drake et al., 1989). For instance, results of drug use assessments are used to estimate drug use prevalence in epidemiological research, contribute to relevant policy formation, and inform individual treatment decisions (Center for Substance Abuse Treatment, 2005, 2009; Regier et al., 1998). Though there are strategies in place which effectively reduce adverse outcomes associated with co-occurrence of schizophrenia and drug use, they require accurate classification of drug use (Drake et al., 2001; Drake et al., 2004). In an effort to increase rates of detection, results of multiple assessment methods, such as self-report, collateral report, clinician interviews, and biological tests, are often used in combination. However, there may be discordance between results and, potentially, an increase in the likelihood of false positives. Furthermore, variables unrelated to drug use, such as participant age, sex, and race/ethnicity, may affect assessment results. To explore these two possibilities, the present study's research aims were to: 1) identify latent classes of concordance/discordance between self-report, collateral report, clinician interviews, and biological tests, and 2) examine participant age, sex, and race/ethnicity as correlates of these classes.

## Summary of Findings

Including and excluding collateral reports, there were high rates of agreement between recommended class memberships. Results also were highly similar in the subsequent bivariate and multivariable analyses. As such, the following sections speak

broadly to the findings derived from both sets of analyses (i.e., those including and excluding collateral reports).

LCA identified four classes of concordant and discordant test results when multiple measures were used to detect drug use in a sample of 1,460 adults with schizophrenia. Classes 1 and 2 were concordant in nature, with high agreement among measures in their classification of drug non-use or use, respectively. Class 1 was comprised of participants with near-zero probabilities of being classified as using drugs by each of the five measures, while Class 2 included participants for whom all measures indicated drug use over half of the time. Classes 3 and 4, in contrast, were discordant in nature. Specifically, Class 3 was comprised of participants for whom biological tests and collateral report indicated non-use while self-report and clinician ratings indicated use. Due to the shorter timeframe of detection for drug urinalysis and collateral report compared to self-report and clinician ratings, some of the disagreement between measures may nonetheless represent accurate results; specifically, participants may have used within the past three months, but not within the last three to four weeks. However, hair RIA affords examination of use in the prior three months – the same timeframe as self-report and clinician ratings – suggesting that discordance observed in this class is not wholly a byproduct of differing timeframes. Class 4 included participants who were classified as non-users by all measures except for hair RIA, which indicated use. Importantly, the discordance observed in Class 4 is not the result of varying detection timeframes, because, as noted above, hair RIA, self-report and clinician ratings all measure drug use over the prior three months.

In addition to the increased rates of detection associated with multi-method drug use assessments (e.g., Drake et al., 1990; see also Swartz et al., 2003), my LCA results suggest that this practice introduces discordance between results. Specifically, for a non-trivial number of participants (15.2% when collateral reports were included, and 19.4% when collateral reports were excluded), drug use measures disagreed in their classifications of users or non-users. Though no prior studies have applied LCA to evaluate drug use measures in adults with schizophrenia – nor, to my knowledge, in the general population – the accuracy of these assessment measures has been examined in samples of adults with serious mental illnesses, the findings of which support my results. Prior research has found self-report and collateral report to effectively discriminate between users and non-users, while casting doubt on the accuracy of biological tests (Wolford et al., 1999). Specifically, in their sample of patients recently admitted to a psychiatric hospital, results of drug urinalysis and medical exams were less accurate than participant self-report and collateral report. More recently, two analyses of the CATIE data have used results of criterion measures (e.g., the SCID for the DSM-III-R and participant self-report) to examine accuracy of single and multi-measure drug use assessment approaches. Here, results showed that biological tests and clinician ratings added just minimal accuracy over self-report alone (Desmarais et al., 2013). Furthermore, the addition of biological tests to self-report led to heightened assessment accuracy for White participants but not for Black participants (Van Dorn, Desmarais, et al., 2012). This last finding, in particular, reflects the possibility that the reliability and validity of drug use measures may differ as a function of participant characteristics.

Indeed, findings of my bivariate and multivariable analyses show differences in participant characteristics across classes. The first set of analyses compared participants in Class 1 with those in Class 2. Because measures were concordant in their classification of non-use and use, respectively, the results illustrate the demographic characteristics associated with drug users versus non-users. Here, findings revealed that drug users were more likely than non-users to be young, male, and Black. These results are generally consistent with those reported in prior studies of drug use among adults with schizophrenia. Younger age and male sex, in particular, are commonly recognized as correlates of drug use in this population (Cantwell, 2003; Kavanagh et al., 2004), as well as the general population (Compton, Thomas, Stinson, & Grant, 2007). In comparison, few studies have examined race/ethnicity as a correlate for drug use in adults with schizophrenia; those that have typically report no significant differences between racial/ethnic groups (e.g., Baldacchino et al., 2009; Sevy et al., 2001; but see Mueser et al., 1990 for an exception). This provides further evidence that the CATIE sample is representative of adults with schizophrenia, and, moreover, supports the validity of my findings.

The remaining bivariate and multivariable analyses compared participants in Class 1 with those in Classes 2 and 3, thus examining the demographic characteristics associated with an increased likelihood of discordance among measure results. Compared to those in Class 1, participants in Class 3 were significantly more likely to be younger in age. Prior research has found younger age is associated with better reliability in self-reporting drug use in this population (Bahorik et al., 2013; Drake et al., 1995). Though it is beyond the scope of

the current project to definitively determine whether members of Class 3 were drug users or non-users, there is a growing recognition of self-report as a valid and viable option for assessing drug use in adults with schizophrenia (Carey & Correia, 1998; Desmarais et al., 2013; Van Dorn, Desmarais, et al., 2012; Wolford et al., 1999). Accordingly, the discordance between measures present in Class 3 is likely due, at least in part, to participant age and its effect on the self-reported drug use.

In comparison to participants classified as non-users, those grouped in Class 4 were significantly more likely to be Black than White. This result is consistent with a number of studies that indicate a bias in hair drug testing due to differences in hair across ethnicities (Borges et al., 2003; Cone & Joseph, 1996; Ledgerwood et al., 2008). Though there is no one accepted explanation for these differences between racial/ethnic groups, it is hypothesized that structural differences across specific hair types lead to selective binding/accumulation of a drug in the hair of Black participants, resulting in a greater likelihood of testing positive for use (Cone & Joseph, 1996). As such, the continued implementation of – and, in some circumstances, sole reliance on – hair RIA in research and clinical practice as the 'objective' measure of drug use assessment is not warranted in all cases.

**Implications**

The latent classes of concordant and, more importantly, discordant drug use assessment results suggest an increased risk of false positives if participants are identified as drug users with at least one positive result. Moreover, findings from bivariate and multivariable analyses show that discordance between drug use assessment results is, in part,

a function of participant age and race/ethnicity. That results may be influenced by factors *other* than drug use suggests the need for further consideration of approaches used to detect drug use in adults with schizophrenia. For instance, other researchers have described concerns over the use of self-report assessment tools originally developed for the general population, which has prompted the development of drug use screening tools specifically for adults with mental illnesses, such as the Dartmouth Assessment of Lifestyle Instrument (Rosenberg et al., 1998). Population-specific instruments, along with tools for evaluating other factors (e.g., sobriety and cognitive impairment) that may affect self-report accuracy in adults with mental illnesses (Carey & Correia, 1998), can together form a "menu of assessment techniques" for clinicians and researchers to reference when deciding which assessment measures to use to maximize reliability (Bennett, 2009, p. 61). Additionally, when multiple measures are used, researchers and clinicians should consider requiring at least two positive test results for an individual to be classified as a drug user; the validity of such a strategy, however, would need to be established empirically. Finally, participants in Class 4 were only identified as users by hair RIA and were disproportionally Black, which brings the objectivity of the measure into question. Regardless the path that policy and practice take, researchers and clinicians should be aware that age and race/ethnicity can affect the likelihood of false positives.

**Limitations**

The present study has several limitations. First, I focused on age, sex, and race/ethnicity in bivariate and multivariable analyses, but other participant characteristics,

such as socioeconomic status, homelessness, and severity of psychiatric symptoms, may distinguish participants between classes. Indeed, age, sex, and race/ethnicity accounted for just 13% of the variance when collateral reports were included, and 12% when excluded. Second, there were 323 participants (22.1%) without hair RIA data at baseline. Similarly, collateral reports were available for only a subset (44.2%) of the full sample. Though the remaining sample is still sufficiently large for LCA (Nylund et al., 2007), there may have been classes that went undetected due to this missing data. Third, participant knowledge that they were going to be providing biological samples may have increased admissions of drug use in their self-reports (Van Dorn, Desmarais, et al., 2012). However, self-report is considered an "essential tool" in detecting drug use and is often implemented in research and practice (Carey & Correia, 1998, p. 744); thus, its inclusion is also a strength of the study. Fourth, the detection timeframes varied by measure; specifically, self-report, clinician DUS, and hair RIA examined use in the prior three months, collateral report in the prior month, and drug urinalysis in the prior one to four days (up to three weeks, based on drug and frequency of use). However, the two discordant latent classes obtained through the LCA did reflect actual disagreement, as the conflicting measures (i.e., hair RIA and self-report/clinician ratings) referenced the same time period. Finally, the CATIE study sample was comprised of adults with schizophrenia willing to take part in a longitudinal clinical trial of antipsychotic medication; generalizability of these findings to untreated adults with schizophrenia (as well as adults with other mental illnesses) is unknown.

## Future Directions

Building upon the current study findings, future research should consider the effects of additional variables, such as socioeconomic status, homelessness, and severity of psychiatric symptoms, on concordance or discordance between results of drug use assessment measures. Additionally, beyond racial/ethnic differences, there is mounting evidence that hair RIA results can be biased by cosmetic treatment and natural or artificial hair color (Cone & Joseph, 1996; Wennig, 2000). Moreover, inclusion of variables reflecting the condition of participants at the time of testing (e.g., cognitive impairment, motivation, and sobriety) may offer further insights regarding how best to conduct drug use assessment in adults with schizophrenia. Also, research comparing self-reports between participants who are and are not providing biological samples will provide a better understanding of the effect of biological testing on the level of disclosure in self-report. Finally, using the same reference period for all assessment measures will limit the possibility of discordant, yet accurate results.

## General Conclusion

This study marks the first application of LCA to evaluate discordance between results of different drug use assessment methods in adults with schizophrenia or otherwise. Additional strengths of the study include the diversity of assessment approaches and the large, representative sample. Findings showed that discordance between results occurs at non-trivial rates and is, in part, attributable to participant age and race/ethnicity. These results may assist in developing population-specific guidelines for drug use assessments to limit

discordance, reduce false positives, and, ultimately, improve detection and treatment of drug use in adults with schizophrenia.

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# APPENDICES

# Appendix A

## Self-Report Measures from the CATIE study

| | |
|---|---|
| **Tobacco/Alcohol/Drug Use** | |
| **In the past 3 months, have you used:** | |
| 6. Tobacco products (e.g. cigarettes, cigars, pipe, chewing tobacco, snuff)? : *(CS06, A1)* | ○ Yes (1) ○ No (0) |
| 7. Alcohol?: *(CS07, A1)* | ○ Yes (1) ○ No (0) |
| 8. Marijuana?: *(CS08, A1)* | ○ Yes (1) ○ No (0) |
| 9. Cocaine?: *(CS09, A1)* | ○ Yes (1) ○ No (0) |
| 10. Opiates?: *(CS10, A1)* | ○ Yes (1) ○ No (0) |
| 11. PCP?: *(CS11, A1)* | ○ Yes (1) ○ No (0) |
| 12. Amphetamines?: *(CS12, A1)* | ○ Yes (1) ○ No (0) |
| 13. Other?: *(CS13, A1)* | ○ Yes, specify (1) ○ No (0) |
| | [ ] *(CS13A, A200)* |
| 14. On average, how many cigarettes per day have you smoked in the past 7 days? *(CSCIGS, N2)* | [ ] *(0-99)* |

# Appendix B

## Clinician Drug Use Scale from the CATIE study

**Clinician Drug Use Scale**

15. Please rate your client's use of drugs over the last three months according to the following scale. If the person is concurrently in an institution, the reporting interval is the time period prior to institutionalization. You should weight evidence from self-report, interviews, behavioral observations, and collateral reports (family, day center, community, etc.) in making this rating.

| | | |
|---|---|---|
| Client has not used drugs during this time interval. | Abstinent = 1 | |
| Client has used drugs during this time interval, but there is no evidence of persistent or recurrent social, occupational, psychological, or physical problems related to use and no evidence of recurrent dangerous use. | Use Without Impairment = 2 | |
| Client has used drugs during this time interval and there is evidence of persistent or recurrent social, occupational, psychological, or physical problems related to use and no evidence of recurrent dangerous use. For example, recurrent drug use leads to disruptive behavior and housing problems. Problems have persisted for at least one month. | Abuse = 3 | |
| Meets criteria for use without impairment, plus at least three of the following: greater amounts or intervals of use than intended, much of time used obtaining or using substance, frequent intoxication or withdrawal interferes with other activities, important activities given up because of drug use, continued use despite knowledge of substance related problems, marked tolerance, characteristic withdrawal symptoms, drugs taken to relieve or avoid withdrawal symptoms. For example, binges and preoccupation with drugs have caused client to drop out of job training and drug social activities. | Dependence = 4 | |
| Meets criteria for dependence plus related problems are so severe that they make non-institutional living difficult. For example, constant drug use leads to disruptive behavior and inability to pay rent so that client is frequently reported to police and seeking hospitalization. | Dependence With Institutionalization = 5 | |

Table 1

*Variables Included in the Present Study*

| **Covariates** | **Operational Definition** |
|---|---|
| Sex | Male (0); Female (1) |
| Age | Participant age (in years) |
| Race/Ethnicity | White (y/n); Black (y/n); Hispanic (y/n); Other (y/n) |
| **Drug Use Measures** | |
| Self-report | Drug use in prior three months |
| | Marijuana (y/n); Cocaine (y/n); Opiates (y/n); PCP (y/n); Amphetamines (y/n); Other (y/n) |
| Collateral Report | Drug use in prior month (according to family member/caregiver) |
| | Non-use (0); Use (1) |
| Clinician Drug Use Scale | Drug use in prior three months (according to clinician) |
| | Non-use (0); Use (1) |
| Hair Radioimmunoassay | Drug use in prior three months |
| | Non-use (0); Use (1) |
| Drug Urinalysis | Drug use in prior one to four days (and up to three weeks) |
| | Non-use (0); Use (1) |

Table 2

*Sample Characteristics Overall and by Latent Class (Collateral Report Included)*

| **Sample Characteristics** | **Total** | | **Latent Classes** | | | | | | | | **Comparisons** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | | 2 | | 3 | | 4 | | |
| | *N* | % | *N* | % | *N* | % | *N* | % | *N* | % | $\chi^2$ |
| *Overall* | 1,460 | 100.0 | 966 | 66.2 | 271 | 18.6 | 76 | 5.2 | 147 | 10.1 | 1,372.827*** |
| *Categorical Variables* | | | | | | | | | | | |
| Sex | | | | | | | | | | | 27.399*** |
| Female | 381 | 26.1 | 283 | 74.3 | 37 | 9.7 | 19 | 5.0 | 42 | 11.0 | |
| Male | 1,079 | 73.9 | 683 | 63.3 | 234 | 21.7 | 57 | 5.3 | 105 | 9.7 | |
| Race/Ethnicity | | | | | | | | | | | 71.674*** |
| White | 722 | 49.5 | 529 | 73.3 | 102 | 14.1 | 44 | 6.1 | 47 | 6.5 | 46.16*** |
| Black | 506 | 34.7 | 274 | 54.2 | 133 | 26.3 | 20 | 4.0 | 79 | 15.6 | 67.65*** |
| Hispanic | 170 | 11.6 | 123 | 72.4 | 25 | 14.7 | 7 | 4.1 | 15 | 8.8 | 3.39 |
| Other/Mixed | 61 | 4.2 | 39 | 63.9 | 11 | 18.0 | 5 | 8.2 | 6 | 9.8 | 1.16 |
| *Continuous Variable* | | | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *F* |
| Age | 1,460 | | 41.73 | 10.99 | 37.35 | 10.60 | 34.20 | 11.27 | 42.07 | 10.45 | 21.178*** |

*Notes*. % = valid percent. Inconsistencies across cells reflect missing data. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 3

*Sample Characteristics Overall and by Latent Class (Collateral Report Excluded)*

| **Sample Characteristics** | **Total** | | **Latent Classes** | | | | | | | | **Comparisons** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | | 2 | | 3 | | 4 | | |
| | *N* | % | *N* | % | *N* | % | *N* | % | *N* | % | $\chi^2$ |
| *Overall* | 1,460 | 100.0 | 959 | 65.7 | 218 | 14.9 | 125 | 10.8 | 158 | 8.6 | 1,301.079*** |
| *Categorical Variables* | | | | | | | | | | | |
| Sex | | | | | | | | | | | 24.599*** |
| Female | 381 | 26.1 | 281 | 73.8 | 31 | 8.1 | 24 | 6.3 | 45 | 11.8 | |
| Male | 1,079 | 73.9 | 678 | 62.8 | 187 | 13.3 | 101 | 9.4 | 113 | 10.5 | |
| Race/Ethnicity | | | | | | | | | | | 67.852*** |
| White | 722 | 49.5 | 527 | 73.0 | 80 | 11.1 | 64 | 8.9 | 51 | 7.1 | 44.89*** |
| Black | 506 | 34.7 | 271 | 53.6 | 108 | 21.3 | 43 | 8.5 | 84 | 16.6 | 65.57*** |
| Hispanic | 170 | 11.6 | 121 | 71.2 | 22 | 12.9 | 10 | 5.9 | 17 | 10.0 | 3.13 |
| Other/Mixed | 61 | 4.2 | 39 | 63.9 | 8 | 13.1 | 8 | 13.1 | 6 | 9.8 | 1.77 |
| *Continuous Variable* | | | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *F* |
| Age | 1,460 | | 41.71 | 11.00 | 37.66 | 10.48 | 34.62 | 11.10 | 42.25 | 10.35 | 22.446*** |

*Notes*. % = valid percent. Inconsistencies across cells reflect missing data. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 4

*Multinomial Logistic Regression Analysis of Class Membership as a Function of Participant Characteristics (Collateral Report Included)*

| Variables | Class 2 vs. Class 1 | | | Class 3 vs. Class 1 | | | Class 4 vs. Class 1 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Estimate | SE | Odds (95% CI) | Estimate | SE | Odds (95% CI) | Estimate | SE | Odds (95% CI) |
| Intercept | -1.077** | 0.335 | - | -0.080 | 0.506 | - | -2.718*** | 0.435 | - |
| Age | -0.035*** | 0.007 | 0.966 (0.953-0.978) | -0.64*** | 0.011 | 0.938 (0.917-0.959) | 0.004 | 0.009 | 1.004 (0.987-1.021) |
| Sex | | | | | | | | | |
| Female[a] | - | - | - | - | - | - | - | - | - |
| Male | 1.005*** | 0.196 | 2.733 (1.862-4.012) | 0.089 | 0.282 | 1.093 (0.630-1.899) | 0.164 | 0.201 | 1.178 (0.795-1.745) |
| Race/Ethnicity | | | | | | | | | |
| White[a] | - | - | - | - | - | - | - | - | - |
| Black | 0.990*** | 0.156 | 2.691 (1.983-3.651) | -0.132 | 0.284 | 0.877 (0.502-1.531) | 1.196*** | 0.200 | 3.305 (2.234-4.890) |
| Hispanic | -0.083 | 0.251 | 0.920 (0.563-1.504) | -0.638 | 0.426 | 0.528 (0.229-1.218) | 0.333 | 0.315 | 1.395 (0.753-2.585) |
| Other race/ethnicity | 0.395 | 0.369 | 1.485 (0.721-3.058) | 0.233 | 0.510 | 1.262 (0.465-3.427) | 0.603 | 0.468 | 1.827 (0.729-4.575) |

*Notes*. Class 1 served as reference group in the analyses. *$p < .05$; **$p < .01$; ***$p < .001$
[a]Reference group

Table 5

*Multinomial Logistic Regression Analysis of Class Membership as a Function of Participant Characteristics (Collateral Report Excluded)*

| Variables | Class 2 vs. Class 1 | | | Class 3 vs. Class 1 | | | Class 4 vs. Class 1 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Estimate | SE | Odds (95% CI) | Estimate | SE | Odds (95% CI) | Estimate | SE | Odds (95% CI) |
| Intercept | -1.381*** | 0.364 | - | -0.192 | 0.423 | - | -2.712*** | 0.423 | - |
| Age | -0.032*** | 0.007 | 0.968 (0.955-0.982) | -0.059*** | 0.009 | 0.942 (0.926-0.959) | 0.006 | 0.008 | 1.006 (0.990-1.022) |
| Sex | | | | | | | | | |
| Female[a] | - | - | - | - | - | - | - | - | - |
| Male | 0.960*** | 0.211 | 2.611 (1.725-3.951) | 0.487* | 0.244 | 1.627 (1.008-2.626) | 0.161 | 0.195 | 1.175 (0.802-1.721) |
| Race/Ethnicity | | | | | | | | | |
| White[a] | - | - | - | - | - | - | - | - | - |
| Black | 1.026*** | 0.169 | 2.791 (2.004-3.888) | 0.298 | 0.216 | 1.347 (0.882-2.057) | 1.183*** | 0.194 | 3.264 (2.233-4.771) |
| Hispanic | 0.055 | 0.266 | 1.056 (0.627-1.780) | -0.625 | 0.362 | 0.535 (0.263-1.089) | 0.396 | 0.299 | 1.486 (0.826-2.671) |
| Other race/ethnicity | 0.323 | 0.415 | 1.381 (0.612-3.115) | 0.402 | 0.421 | 1.494 (0.655-3.410) | 0.526 | 0.466 | 1.692 (0.678-4.222) |

*Notes*. Class 1 served as reference group in the analyses. *$p < .05$; **$p < .01$; ***$p < .001$
[a]Reference group

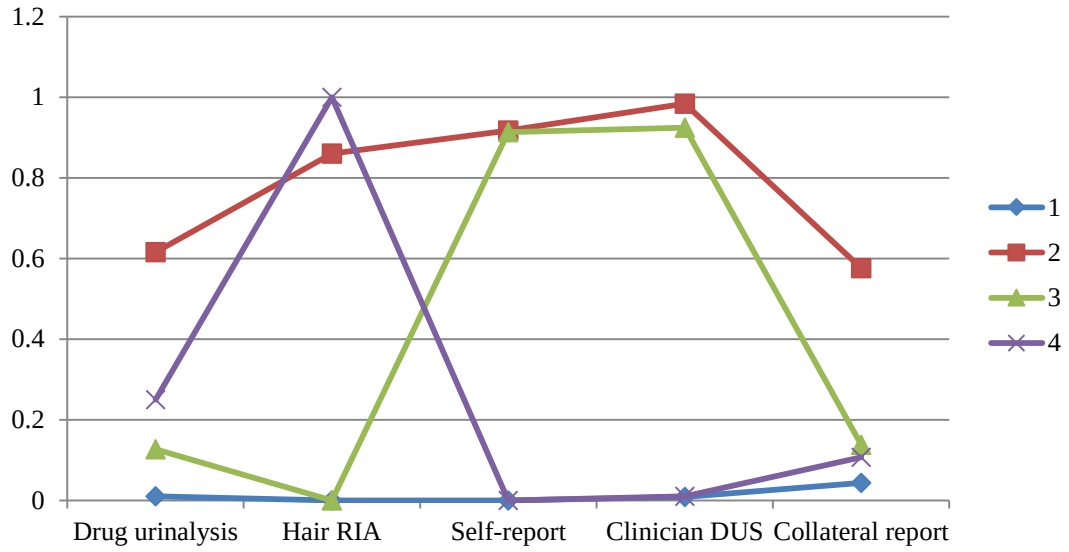


*Figure 1.* Conditional probabilities of drug use assessment measures (collateral report included)

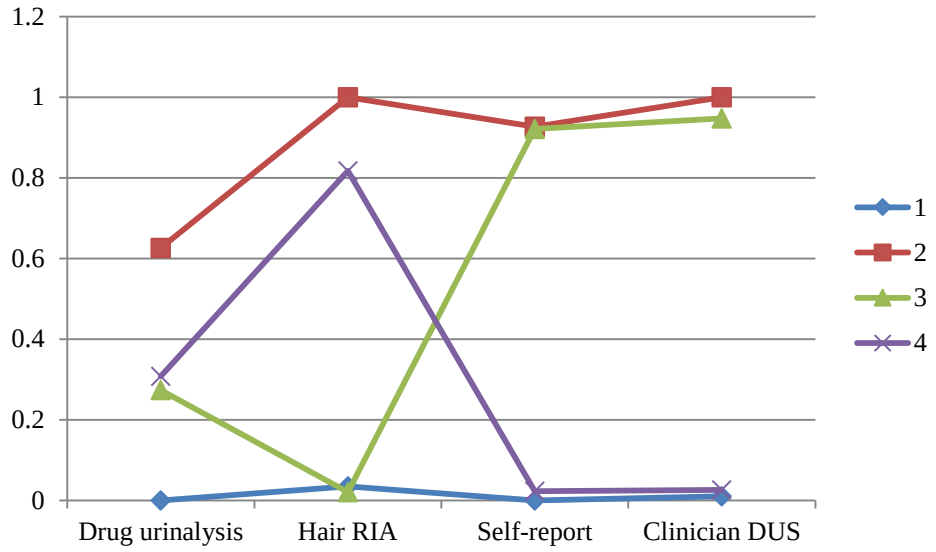


*Figure 2.* Conditional probabilities of drug use assessment measures (collateral report excluded)