Exploring the Utility of an Estimation Procedure to Reveal Drug Use among Arrestees: Implications for Service Delivery

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Abstract

One of the most persistent questions plaguing researchers and service providers is how to best estimate the extent of targeted behaviors in relevant populations. One problem of particular importance is the prevalence of drug use in justice-involved populations. Data have been collected through such methods as self-report and analysis of biological specimens, although both have notable limitations when used alone. As a means of drawing on the strengths of both methods, such data can be used in a confirmatory manner or, alternatively, may be summed to estimate prevalence. However, this latter approach is not without difficulty as different sources lack substantial agreement. The focus of this study is to employ a methodology that utilizes multiple data sources and adjusts for nonreporting from either source. Compared to more commonly employed techniques, the results indicate that the alternative method yields higher estimates of marijuana and cocaine use among a sample of arrestees. These findings, in turn, suggest that current behavioral health interventions and policies may be based on underestimates of drug use.

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Introduction

There is overwhelming evidence that drug use is common among those who are arrested and incarcerated. Approximately one-third of state and 26% of federal inmates indicated that they were under the influence of drugs during the commission of the crime for which they were incarcerated. In addition, 21% of state and 55% of federal inmates are serving time for drug use violations.[1] Data from local jails further corroborate the notion that drug use is a major problem among criminal justice populations.[2] These high levels of drug use extend well beyond the individual offender. For instance, drug use is a risk factor for recidivism,[3] which is related to increases in direct costs (i.e., more police on the streets, larger dockets in courts, and re-incarceration) and indirect costs (e.g., subsequent victimization) that are incurred by the public.

One cost-effective means of addressing the problems associated with drug use among those arrested or convicted of a crime is drug treatment programs.[4] Unfortunately, such treatment is not widely available in general[5] and is even more scarce among individuals who are incarcerated.[6] Yet, there is evidence that many who are incarcerated have substantial drug use problems. For instance, 53% of state and 45% of federal inmates meet the Diagnostic and Statistical Manual of Mental Disorders criteria for drug dependence and abuse.[1] Belenko and Peugh indicated that 70.4% of male and 76.8% of female inmates in state prisons are in need of some form of drug treatment intervention. However, the data also revealed that less than one-third of those in need received any form of treatment since their admission.[1]

Because of the convergence across studies indicating that drug use is widespread in correctional populations and that treatment services and resources are lacking, it is important that the means of determining prevalence are considered further as they have important implications for the needs assessments that should inform planning and programming decisions. Indeed, it is likely that many, if not most, prevalence estimates that are typically relied upon may be inaccurate. For instance, self-reports provide an invaluable method for measuring the incidence, prevalence, and patterns of illicit drug use, in large part because the individual possesses knowledge not necessarily shared by others.[7,8] By the same token, self-report methodologies have been criticized frequently because they are premised on the respondent accurately reporting on sensitive and highly stigmatized behavior. Such concerns are even more pronounced in criminal justice settings where real or perceived punitive actions may result from admission of drug use.[9,10] Importantly, much of what is currently known about the need for drug treatment programs among those who are involved in the justice system is based on self-report.[1,6]

Given the reliance on self-report surveys as a measure of drug use prevalence among incarcerated populations, it is crucial that these measures be validated in some way. This requires a comparison to some method that is presumably more accurate.[11] Ideally, self-reports could be compared to some "gold standard" of drug use prevalence as a means of validation. Unfortunately, no such gold standard exists. However, Mieczkowski and colleagues have suggested that self-reported drug use might be validated against some method of objective physiological testing.[12] One promising method in this regard is to test biological specimens for the presence of drugs. Urine tests are the most commonly used method for identifying drug users, but drugs have also been detected in blood, saliva, semen, sweat, and hair.[8,9,12–14]

According to Mieczkowski, validation researchers have generally expressed the degree of validity as a percentage, specifically, the number of concordant responses divided by the total number of responses.[8] Early validation research typically affirmed the accuracy of self-report surveys of drug use; no validation study ever reported less than a 70% concordance rate, and many reported validation percentages of 90% or higher. However, starting in the early 1980s, data on self-reported drug use derived from survey research was for the first time subject to bioassay comparison. In these studies, self-reported drug use was compared to more objective measures such as urinalysis, which could identify the presence of certain drugs within the urine. This wave of

research, led by Wish and others, revealed that self-reported drug use was often undercounting apparent use, at least as indicated by the bioassay results. Early data from the National Institute of Justice Drug Use Forecast (DUF), for example, routinely showed that cocaine use was under-reported by as much as 50% in many cities that were DUF sites. Ultimately, this led the U.S. General Accounting Office to recommend that self-reports be validated with more objective measures, such as urinalysis and hair testing.[8,15,16]

The first large-scale study to assess the validity of self-reported drug use was the DUF study.[11,16,17] One purpose of the DUF project was to create a data source that allowed for a series of validation studies comparing illicit drug use data gathered from the hair and urine tests with self-reported surveys.[12] The DUF study consistently found that only about half of those who test positive for a drug report use in the past 2 to 3 days.[11] Such findings suggested that sole reliance on self-reports will fail to capture the true extent of drug use and illustrated the need for further consideration of prevalence estimates in the context of multiple data sources.

Although the use of bioassays can provide an independent means of assessing drug use, even this methodology suffers from drawbacks. For example, despite being widely accepted as a valid measure of drug use, urinalysis has limitations in terms of what it can reveal about the validity of self-reports.[11,18] The most notable limitation for the purposes of prevalence estimation is the fact that many drugs of abuse (e.g., heroin, cocaine) are rapidly excreted from the urine.[18] The limitations of urinalysis and the advancement of immunoassay technologies have led to an increase in the use of hair assays in drug use prevalence estimation and self-report validation.[18,19] Hair assays are more appropriate indicators of long-term drug use and intensity vis-à-vis urinalysis, as this method is not susceptible to false negatives stemming from drugs that are rapidly excreted from urine.[10,12,18,20] However, some drugs (e.g., cannabis) are difficult to detect from a hair assay.[10] This establishes the strategic reality that additional and distinct methods remain important in crafting the most accurate estimates possible. These studies also support the development of bioassays that are matched to time- and drug-specific questions, which can improve on estimates from measures of self-reported drug use alone.[21]

As the above review suggests, neither self-reports nor bioassays are wholly accurate and both have inherent problems.[11] Instead of relying on only one measure of use, a more promising approach is to use multiple methods and sources in an effort to triangulate the behavior.[22–24] Thus, using both self-report and bioassay methods may offer better estimates of drug use prevalence than either one alone. The question arises, however, of how best to use multiple measures most efficiently and appropriately. Commonly, the approach applied to multisource data is either confirmatory or additive. In the first case, researchers simply utilize these data as a means of assessing concurrent validity, as was noted above with the National Institute of Justice-funded studies assessing the correspondence between self-report and hair and urine tests.[11] In another example of this approach, Hindelang, Hirschi, and Weis examined the correspondence between self-reports and official reports of delinquency in a sample of several thousands of Seattle youth.[25] In both of these approaches, the researchers accepted a response as valid only when both sources were in agreement. Although the confirmatory strategy can provide some useful insights, it also suffers from a notable drawback; it fails to utilize all of the available information. That is, if the sources do not converge, then the data are not used.

Failure to use the data on which the two sources disagree, however, can lead to dramatic underestimates of prevalence because it is uncommon for both sources to agree in a majority of cases.[26] To avoid this problem, a researcher may choose to treat any affirmative response as an indication that the behavior has occurred.[27] This is referred to as an $A+B+C$ (or additive) approach where A represents the instance where both the primary and collateral report the behavior, B represents the situation where only the collateral report is affirmative, and C reflects an affirmative report from the primary source that is not confirmed by the collateral. Thus, this approach simply sums the affirmative responses. The case where both reports are negative does not figure into the

calculation. The additive approach, then, does not suffer from the same drawback as the confirmatory approach because more data are utilized.

Drawing on work in epidemiology, Lidz et al. have recently argued that the additive approach produces underestimates as well.[28,29] They suggest an alternative means of assessing prevalence from multiple data sources that makes an adjustment to enhance such estimates. Specifically, it adds ($B \times C/A$) to the "$A+B+C$" calculation discussed above. This term represents a correction for the proportion of cases where the two reporting methods disagree, divided by the number of cases where both reports are in agreement. Thus, the ratio of disagreement to agreement in the observed multisource reports is factored into the estimates. This value is intended to adjust the prevalence estimate to account for cases where neither report captures the behavior (i.e., nonreporting), but it actually happened. Consequently, like a regression equation, it is inherently an estimate that draws on the data and also some unobservable error. Lidz et al. found that this alternative approach yielded more accurate estimates of violence among a psychiatric sample. As with drug use, there is no gold standard for assessing the prevalence of violent behavior in a given population. To overcome this, they presented a series of hypothetical scenarios in which the "true" prevalence was known. This alternative method produced higher estimates of violence than the more commonly used additive approach and was thus a more accurate estimate in the sense that is was closer to the "true" extent of violence. This finding persisted whether the researchers looked at the prevalence of violent behavior among individuals or the actual number of violent events.

The present study employs this alternative approach to estimate the prevalence of drug use among arrestees. Utilizing measures based on self-report, urinalysis, and hair specimens, this study applies the Lidz et al. approach in order to assess the estimates obtained with that procedure relative to those obtained with more frequently used methods for dealing with multiple source reports of behavior. In doing so, the analysis illuminates some key issues in drawing from only one data source in estimating prevalence. Again, it is important that prevalence estimates are considered in the context of program needs as, ideally, such information will be used in setting policy and implementing programs.

Method

The specimens and survey data were collected during the operation of The Pinellas Drug Use Forecast Study, a drug-monitoring program conducted at the Pinellas County Jail in Largo, Florida. All cases comprise arrestees booked into the county jail. The sample was stratified into the following categories: nondrug felony cases (approximately 64%), drug felony cases (approximately 20%), and driving under the influence of intoxicants cases (approximately 16%). Study staff interviewed 1,269 male and female arrestees at the booking stage of arrest over the course of four waves of data collection. All interviews were anonymous and no results were used as evidence for any charges or other action by legal officials. The data collection procedure required that individuals were asked to self-report their drug use prior to being asked to give urine and hair specimens. This ensured that the self-report response was not affected by the looming physical test of substance use. Despite being voluntary, more than 95% of those approached agreed to take part in the study. As might be expected, some prospective participants were willing to self-report their use or lack of use, but not supply physical samples for testing. Specifically, a small number of those who agreed to participate in the self-report portion of the study did not provide urine (1.2%) or hair (8.5%) samples.

The data utilized for the analysis include the rates of self-reported cocaine and marijuana use over short-term (48 h) and long-term (30 days) retrospective windows, urinalysis for marijuana and cocaine, and hair assay for marijuana and cocaine. Of the 1,269 arrestees in the sample, 1,189 provided adequate samples for marijuana urinalysis and 599 provided adequate samples for

marijuana hair analysis, while 1,191 arrestees provided adequate urine samples for cocaine detection and 910 provided adequate hair samples for cocaine detection.

There are two important issues to bear in mind in considering the use of bioassays as a marker of possible drug use and as a comparator for purposes of evaluating self-reported drug use. First, like any diagnostic indicator, some threshold value must be established to indicate that the drug is present. This value is typically referred to as the "cutoff value" and represents the lowest concentration at which a specimen would be considered "drug positive." The values utilized in this study are based on the United States Federal Government's promulgated standards for urinalysis. Cut-offs for hair analysis are based on the standards established by the International Association of Forensic Toxicology. Second, the methods by which the biospecimens are collected and analyzed evince differential sensitivities to particular drugs and time frames. In the case of urine, the drug appears relatively quickly and is gone relatively quickly. Hair, in contrast, is a very stable matrix for cocaine (less so for cannabinoids) and can be detected for an indefinite period of time. Thus, the interaction between the window of detection and drug type provides a key consideration in the choice of the optimal means of assessing use.

Cocaine and marijuana

In considering both urine and hair as specimen for toxicological tests, in conjunction with the principles discussed in the previous paragraph, it is important to note that this study examines drugs with two very different characteristics in terms of excretion, and consequently, detection. Cocaine is a drug with relatively rapid excretion characteristics. Marijuana (or other cannabinoid variants such as hashish) is a drug with relatively slow excretion rates. Marijuana is often detected for several weeks after cessation of use in chronic consumers. Testing a population using both hair and urine, and interpreting those results, needs to be tempered by considering the properties of these individual drugs. In this study, multiple drugs (marijuana, cocaine), information sources (self-report, hair assay, urine screen), and time windows (48 h, 30 days) are utilized to demonstrate the use of the Lidz et al. model in the context of substance use among justice-involved persons.

Data analysis

The current analysis begins by examining the univariate descriptive statistics of the three measures of drug use over both short- and long-term retrospective windows. After gaining insight into the prevalence of these measures, the analysis focuses on the agreement and/or disagreement between self-report and bioassay measures of drug use. In comparing the outcome of self-report and bioassay, the simple presentation of two by two tables is used—contrasting the admission or denial of use with the results of a bioassay, either hair or urinalysis. The prevalence of use is then calculated for both marijuana and cocaine, over the short- and long-term review periods, using both the additive $(A+B+C)/N$ and the alternative methodology $(A+B+C)/N+B\times C/A$ suggested by Lidz et al., which corrects for nonreporting across sources. The final stage of the current analysis compares the results of the two prevalence estimations. Based on the findings of Lidz et al., it is predicted that the alternative method will yield higher, more accurate estimates of drug use among arrestees in this study (Table 1).

There are two important factors to bear in mind when examining the tables and the respective drugs on which they report. The first is the retrospective windows and suitability of the particular biological specimen. As noted above, urinalysis works well for marijuana and less well for cocaine due to their respective pharmacodynamics. Hair has the opposite configuration. It works well for cocaine and less well for marijuana. Secondly, the willingness to admit to the use of a particular drug may be tied to the relative social stigmatization attached to it. Based on these factors, there are several predictions one can make about how the tabular arrays will turn out. First, it is more likely

Table 1
Additive and alternative methods of prevalence estimation

		Source 2	
		Yes	**No**
Source 1	Yes	A	B
	No	C	D

D is not used in the estimation calculation. Additive method: $A+B+C$=affirmative; alternative method: $A+B+C+(B\times C/A)$=affirmative

that people will admit marijuana use than cocaine use. Second, it is expected that marijuana users will be more readily identified with urinalysis and cocaine users with hair analysis.

Results

The first set of analyses focused on the prevalence of marijuana use. With respect to short-term marijuana detection, 188 (16%) respondents indicated that they had used marijuana within the past 2 days. The urinalysis, however, indicated that 466 (39%) had recently used. As shown in Table 2, there were 139 cases in which the self-report and urinalysis were in accord, representing a 27% concordance rate. Using the standard additive method (i.e., $A+B+C$), there were 515 individuals who could be described as having recently used marijuana. However, using the alternative method yields a prevalence of 630 recent marijuana users, which is a 22% difference. By way of comparison, self-reported marijuana use captures only 30% of the prevalence estimate provided by the alternative method, while the use of urinalysis alone would encompass 74% of this estimate.

The results for long-term marijuana detection (see Table 3) were comparable to the short-term analyses described above. For instance, prevalence estimates of self-reported marijuana use within the past 30 days were lower (n=178; 30%) than the bioassay estimates (n=217; 36%). However, the concordance rate (in which both self-reported drug use and positive bioassays agreed) was relatively higher (45%) than it was in the short-term analyses described above. In terms of multisource method prevalence estimates, the additive approach yielded an estimate of 272 marijuana users. Conversely, the alternative method indicated there were 314 marijuana users in the sample, which is a 15% increase. When examining the relative efficacy of each measure of drug use detection to capture the estimate provided by the alternative method, once again both self-reports (57%) and bioassays (69%) provided underestimates.

Table 2
Prevalence estimates for marijuana use within the past 2 days

		Urinalysis	
		Yes	**No**
Self-reported marijuana use	Yes	139	49
	No	327	668

n=1,183. Additive method prevalence estimate=515 marijuana users; alternative method prevalence estimate=630 marijuana users

Table 3
Prevalence estimates for marijuana use within the past 30 days

		Hair analysis	
		Yes	**No**
Self-reported marijuana use	Yes	123	55
	No	94	327

n=599. Additive method prevalence estimate=272 marijuana users; alternative method prevalence estimate=314 marijuana users

The next set of analyses focused on short- and long-term estimates of cocaine use. For short-term cocaine detection (see Table 4), 9% (*n*=112) of the sample admitted to using cocaine within the past 2 days. The bioassays, however, suggested that many more arrestees had used within that time frame (*n*=257; 22%). The two detection methods were concordant 41% of the time. Next, the two prevalence estimation methods were computed and compared. The additive approach indicated that there were 262 arrestees who had recently used cocaine, while the alternative method yielded a prevalence estimate of 269. This represented a fairly modest difference (3%). Relying on self-reported cocaine use only would underestimate recent use (42%). Conversely, the bioassay results were able to identify nearly all of the recent users (96%) identified with the Lidz et al. prevalence estimate approach.

Finally, prevalence estimates were examined for long-term cocaine detection. As shown in Table 5, 117 (13%) respondents self-reported cocaine use within the past 30 days. Once again, the bioassay results indicated a much higher prevalence of cocaine use (*n*=380; 42%). Unlike the short-term cocaine use results presented above, the concordance rate for self-reports and bioassays was much lower (24%). With respect to the two methods being examined in this study, the additive approach yielded a prevalence rate of 400 arrestees who had used cocaine within the past 30 days. The alternative method indicated that this was (once again) an underestimate. Specifically, the estimate from the alternative method was 15% greater (*n*=458). Based on this alternative estimation, both self-reports (26%) and bioassays (83%) provide underestimates of cocaine use within the past 30 days.

Discussion

The purpose of this study was to examine the efficacy of different approaches to assessing prevalence of drug use. To this end, this study focused on the prevalence of two different types of

Table 4
Prevalence estimates for cocaine use within the past 2 days

		Urinalysis	
		Yes	**No**
Self-reported cocaine use	Yes	107	5
	No	150	928

n=1,190. Additive method prevalence estimate=262 cocaine users; alternative method prevalence estimate=269 cocaine users

Table 5
Prevalence estimates for cocaine use within the past 30 days

		Hair analysis	
		Yes	**No**
Self-reported cocaine use	Yes	97	20
	No	283	509

n=909. Additive method prevalence estimate=400 cocaine users; alternative method prevalence estimate=458 cocaine users

drugs (i.e., marijuana and cocaine) in an arrestee sample. In addition, drug use for both short- and long-term time frames (operationalized as 48 h and 30 days) was explored. Many studies of prevalence have relied on single sources of information (e.g., self-reported drug use). Other studies draw on multiple sources (e.g., self- and informant-reports), but use this information in an additive manner.[27] Prevalence estimates based on an additive model simply treat any indication of drug use as positive, and all positive responses are summed to create the estimate. A relatively new methodology that adjusts for nonagreement across sources was utilized in this study and compared to the aforementioned approaches.

In every instance, this alternative approach produced higher estimates of drug use than other methods (e.g., a simple additive approach). Although it cannot be definitely stated that the estimates produced with the alternative approach provide a more accurate indication of prevalence, there are reasons to believe it does. Lidz et al. conducted a series of hypothetical analyses in which the prevalence of the behavior was known, and then compared the prevalence estimates based on the different methodologies. The alternative method was the most accurate. Thus, it can be reasonably concluded that the application of this method to the current data also provides an accurate estimate of drug use among the arrestees included in this sample. More specifically, the alternative approach indicated that marijuana and cocaine use were more prevalent than estimates based on self-report or bioassays alone. This was particularly true when examining marijuana use. Additionally, in all cases, it was clear that a simple confirmatory approach where the tests are used to validate or invalidate the self-report responses would be extremely problematic and result in prevalence estimates well below what either the additive or Lidz et al. approaches suggest.

Implications for Behavioral Health

These findings are important for a number of reasons. First, provision of necessary services is fundamentally based on a valid needs assessment. A needs assessment, in turn, is based on an accurate understanding of the extent of the problem. Using the more common approaches in which prevalence is underestimated would lead to fewer resources than would be necessary. However, it is important to note, for research and planning purposes, that this approach accounts for aggregates of use in the population as a whole and not individual behavior. Consequently, it must be viewed as a planning tool for estimating the prevalence of a problem rather than as a means of determining whether reported use is accurate or inaccurate in a given case.

The discussion at the outset of this paper highlighted the considerable treatment needs of justice-involved individuals. Lest this be taken as a purely academic enterprise, it is important to couch the prevalence estimates in the context of needs assessment. SAMHSA estimated that it costs an average of $2,941 per drug treatment episode for justice-involved individuals.[30] First, considering the additive estimation approach, assuming that each user requires treatment (which may not truly

be the case), and drawing on the self-report and hair analysis estimates reported in this study for 30-day cocaine use, yields a total estimated dollar need of $1,176,400 (400 users at $2,941 per user). Looking at the estimates that draw on the Lidz et al. approach, there is an increase to 458 users, which moves the monetary service need to $1,346,978. This is a nontrivial difference. Although programs may not be likely to obtain the needed resources in either case, the latter approach, in conjunction with multisource measurement, provides an estimate that accounts for issues of recall, truthfulness, and precision in data sources. Clearly, getting the best estimates of prevalence is an essential first step in conveying service needs to decision-makers and, as demonstrated in this study, the differences between the means of capturing drug use prevalence may have important implications for services planning. Certainly, individual decisions would still need to be made regarding treatment at the case level, but this approach can provide a sense of resources required at the organizational level.

Second, moving beyond service delivery, this alternative methodology provides more accurate estimates that can inform epidemiological studies. While this study focused on drug use, there are no a priori reasons to indicate this alternative method could not be used in the assessment of other behaviors (e.g., rates of offending, victimization, psychopathology). Third, this application underscores the importance of obtaining data from multiple sources. The results demonstrated fairly sizeable differences across methods. Clearly, the use of multiple sources of information can help to counteract the biases inherent in each singular method, and as indicated in the current investigation, can yield more accurate estimates. The adjustment used in this study offers further backing in ensuring proper prevalence estimates. For all these reasons, this study has appeal to both basic and applied researchers and practitioners.

This study is surely not the first to endorse the scientific utility of collecting data from multiple sources. In fact, triangulation is a mainstay of solid scientific practice. However, it is also more costly than acquiring data from only one source. Thus, researchers and practitioners need to consider both the costs and benefits of this approach. With respect to the current analysis, the different estimates for marijuana and cocaine offer two, competing suggestions. There were more notable differences in estimates when examining marijuana use, which suggests that using multiple sources may be a better approach. Additionally, it is important to note that marijuana and its metabolites have a relatively long half-life in the urine when compared to cocaine. Thus, the use of a 48-h self-report when considering urinalysis will tend to produce a "false positive" in that the person may be accurately reporting their nonuse within the last 2 days, but produce a cannabinoid positive urinalysis from an earlier use of the substance. However, when examining cocaine use, the bioassays alone produced reasonably accurate prevalence estimates. Thus, expending the necessary resources to acquire self-report data on cocaine use might not be cost-effective.

It is also important to carefully consider the specific purpose of drug testing, especially as this pertains to bioassays. For instance, if an employer simply wants to know whether an employee has recently used some substance, a urinalysis is more cost-effective. Hair analysis may be more appropriate in other instances. For example, if an arrestee is placed in a long-term drug treatment facility 2 weeks after being arrested, a urinalysis will not likely yield the necessary information to conduct a useful assessment for that individual. This is because most drugs are quickly excreted, and a urinalysis will test negative. This, however, does not provide any sense of long-term drug use, which offers much more information for treatment purposes.

While informative, this analysis is not without limitations. Lidz et al. have identified some of the weaknesses of this alternative estimation approach. First, they note that this method assumes that the sources of information are independent. In the current analysis, this seems to be a reasonable assumption in that self-report data are independent from bioassays. However, future efforts that use this methodology should take care in confirming the independence of the data sources. Another limitation they describe is the manner in which such estimates can be used in inferential statistical analyses. Specifically, there are currently no algorithms that exist in statistical software packages

that can readily compute this estimate, particularly when there are a variety of sources of data. They also note that this method assumes no false negatives. While this should not have been a substantial problem in the current analysis because bioassays are reasonably accurate, they are not foolproof. As such, the estimates produced using the alternative method probably still underestimate the true prevalence. By the same token, it is likely that they come closer to the true prevalence than other, more frequently used methods.

The approach is applied in this study as it would be used in common practice. This means that there is no way to be certain about the true prevalence of a behavior (i.e., no "gold standard" indicative of the true population value). Thus, the results attained using this method cannot be fully gauged against any fixed population parameters and must be observed with the assumptions in mind. All in all, these are still estimates, which should be kept in mind when considering implications. An overarching limitation is that the data come from arrestees at one location, thereby limiting generalizability. Also, data were based on self-reports and bioassays of marijuana and cocaine use. Future studies should focus on other sources of information and drugs to ascertain the extent to which this alternative method produces superior estimates.

The limitations notwithstanding, this study provides an interesting and unique means of maximizing data to assess the prevalence of drug use. Moreover, this estimation procedure is relatively easy to implement, requiring only a minimal adjustment in the equation. Ultimately, however, its practical utility will be premised on the likelihood that it will be used by researchers and practitioners. Hopefully, this study serves as a helpful guide and researchers and program officials can begin using this new methodology to develop a greater understanding of those clients to whom they must provide services.

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