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Trends and Correlates of Discordant Report of Drug Use among Nightclub/Festival Attendees, 2019-2022

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Abstract
Introduction: People who attend nightclubs and festivals are known for high prevalence of party drug use, but more research is needed on underreporting in this population, in part, because unintentional drug exposure through adulterated drug product is common.
Methods: Adults (age ≥18) entering nightclubs and festivals in New York City were asked about past-year drug use in 2019-2022 (n=1,953), with 328 providing an analyzable hair sample for testing. We compared trends in self-reported drug use, drug positivity, and 'corrected' prevalence adjusting for unreported use, and delineated correlates of testing positive for ketamine and cocaine after not reporting use (discordant report).
Results: Cocaine and ketamine were the most frequently detected drugs (55.2% and 37.2%, respectively), but these were also the two most underreported drugs, with 37.1% and 26.4%, respectively, testing positive after not reporting use. Between 2019 and 2022, positivity decreased for cocaine, ketamine, MDMA, and amphetamine, and underreported exposure to cocaine and ketamine also decreased (ps<.05). Underreporting of use of these drugs was common, but we also detected underreported exposure to MDA, methamphetamine, synthetic cannabinoids, fentanyl, and ethylone. Prevalence of discordant report of cocaine use was higher post-COVID (aPR=1.88, 95% CI: 1.07-3.32) and lower among those reporting ecstasy (aPR=0.52, 95% CI: 0.28-0.99) or cocaine use (aPR=0.17, 95% CI: 0.07-0.46). Prevalence of discordant report of ketamine use was lower post-COVID (aPR=0.37, 95% CI: 0.15-0.87) and among those reporting cocaine use (aPR=0.56, 95% CI: 0.33-0.95). Compared to self-report alone, estimated decreases between 2019 and 2022 were larger for corrected prevalence of use of cocaine (-38.4% vs. -34.4%) and ecstasy (-26.9% vs. -21.5%).
Discussion: Underreporting of drug use was common, suggesting the need for researchers to better deduce intentional underreporting vs. unknown drug exposure via adulterants.
Conclusions: Researchers should consider both self-report and toxicology results from biological samples when estimating trends in drug use.

Keywords: club drugs; hair testing; cocaine; ecstasy; ketamine

INTRODUCTION

Evidence regarding the prevalence of drug use is important in informing prevention, treatment, and harm reduction efforts. The main method used to estimate prevalence of drug use is self-report (e.g., via surveys). For example, national surveys are the main source for estimating trends in incidence of drug exposures (1, 2). However, underreporting of drug use is common as survey responders may fear disclosing it; others may simply not recall use, and some individuals may simply not understand (or not closely read) questions about drug use (3-5). Further, drugs such as ecstasy and heroin, historically, tend to be adulterated with other substances, so it is also common for people who use to have been unknowingly exposed to adulterant drugs (6-13). One way to help counter underreporting on surveys is to incorporate biospecimen testing of participants to inform estimates of use (13). While biospecimen results on their own can indeed be informative regarding monitoring and estimation of trends and pattern (14-16), a combination of surveys and biospecimen testing may be most efficacious. However, more studies combining such methods are needed.

Nightclub and dance festival attendees are a somewhat unique population as they are at high risk not only for use of common party psychoactive substances such as ecstasy/MDMA, cocaine, and ketamine (17-19), but also at high risk for being unknowingly exposed to adulterants or contaminants (including NPS) (11-13, 20). Focusing on trends in both reported and unreported drug use in this population can not only possibly provide insight regarding trends in exposure in the general population (21), but it can also inform prevention and harm reduction efforts.

In this analysis, we focused on use of a wide variety of drugs with a particular attention on six of the most common molecules used in the nightlife population— cocaine, ecstasy/MDMA, ketamine, amphetamine, methamphetamine, and 3,4-methylinedioxyamphetamine (MDA) (17, 22). We focused on these drugs not only because prevalence was high enough to examine trends, but also because some of them have been linked to adulterated products or underreported exposure in past studies (6, 7, 12, 13). Results from surveys and hair analysis were compared. In hair samples, the afore mentioned substances are easily detected, unlike, for example, LSD (23-25). Further, since adulterated and contaminated drugs are of concern, the presence of the substances above the limits of detection was used to identify positive samples, rather than standard cutoffs (https://pubmed.ncbi.nlm.nih.gov/27402378/). This is because very small amounts of drug detected in particular may suggest unknown exposure to small amounts mixed in with other drugs.

METHODS

Procedure

Adults about to enter nightclubs and dance festivals in New York City were surveyed from 2019-2022 (*n*=1,953) using time-space sampling. Events were randomly selected from an ongoing list of parties promoted on a popular electronic dance music (EDM) party ticket website and also based on recommendations from key informants (17). Individuals were eligible if they were age ≥18 and about to enter the selected venue. At the point of recruitment, participants provided informed consent and took an anonymous survey on a tablet. Participants were surveyed entering 115 events and the overall survey response rate was 69%. Participants were also asked if they were willing to provide a hair sample for future analysis. Those completing the survey were compensated $10 USD and those providing a hair sample were offered an additional $5 USD. A quarter (24.9%, n=486) of participants provided a hair sample, and 328 were large enough to analyze (67.5% of those submitted and 16.8% of the full sample). All methods were approved by the New York University Langone Medical Center institutional review board.

Measures

Participants were asked about their age, sex, race/ethnicity, and sexual orientation, as well as their frequency of EDM event attendance in the past year. Participants were also asked about past-year use of drugs including cocaine, ecstasy (MDMA/Molly), ketamine, amphetamine (nonmedical use), methamphetamine, and MDA. Molly was added to the definition of ecstasy as this is a common name for this drug in the US (26).

Hair Analysis

Hair samples were tested via published methods using ultra-high performance liquid chromatography–tandem mass spectrometry (UHPLC-MS/MS) (27, 28). A full list of targeted analytes is presented in Supplemental Table 1. However, in our analysis of samples collected in 2021-2022, we also utilized untargeted high-resolution mass spectrometry (HRMS)-based screening, which allowed for qualitative identification of NPS not in our library (29). In this analysis, we focused primarily on detection of cocaine, MDMA, ketamine, amphetamine, methamphetamine, and MDA as these were among the most common drugs detected, allowing for trend analyses. Given that exposure to adulterated or contaminated drugs was of interest, we set the limits of detection as the minimum criterion to identify positive samples. The exception was cocaine in which we only considered samples positive if at least 0.5 ng/mg was detected in addition to the presence of benzoylecgonine or cocaethylene (30). Further, since MDA is a metabolite of MDMA, we conservatively estimated MDA positivity (not detection as a mere metabolite) when the ratio of MDA ng/mg to MDMA ng/mg was ≥0.2 (31, 32). Hair samples were analyzed in their full length up to 12 cm, representing up to a 12-month timeframe (33).

Statistical Analyses

First, we calculated descriptive statistics to describe the study sample, and we used chi-square and independent samples t-test to determine whether there were differences in sample characteristics according to whether an analyzable hair sample was provided. We then calculated the prevalence of drug positivity and discordant report—defined as testing positive after not reporting use. We first did this for all drugs detected (within those providing an analyzable hair sample) and then also by year for the six main drugs of interest—cocaine, ketamine, MDMA, MDA, amphetamine, and methamphetamine. For these drugs, we also examined trends in positivity and discordant report between 2019 and 2022. Three methods were used to examine trends. First, we compared prevalence in 2022 to 2019; second, we tested for linear and quadradic trends; and third, we determined whether there were shifts between post-COVID years (2021-2022) and pre-COVID years (2019 through early 2020). All of these models controlled for participant sex, age, race/ethnicity, sexual orientation, and type of venue where recruited (nightclub vs. festival).

For the main six drugs of interest, we then compared any detection and level of detection of each drug according to whether past-year use was reported. Regarding any detection, we determined whether there were bivariable differences in detection vs. no detection according to whether use was reported, and then we further examined whether use was related to any detection in multivariable generalized linear models (GLMs) using Poisson and log-link which generated an adjusted prevalence ratio (aPR) for use in relation to any positive detection. For level of detection (among positive cases), we first compared level of detection according to whether use was reported using Mann-Whitney U tests for nonparametric (e.g., highly skewed) distributions. We then examined these associations in multivariable GLMs (using a gamma distribution and log-link) with robust standard errors. All of these multivariable models controlled for year, participant sex, age, race/ethnicity, sexual orientation, type of venue where recruited, and hair length.

Next, we delineated correlates of discordant report of cocaine and ketamine use. As such, first we tested for differences between each covariate of interest and whether there was discordant report using chi-square and independent samples t-test, and then all covariates were fit into multivariable GLMs using Poisson and log-link. Finally, we sought to estimate trends in prevalence of use of each drug in the population based on self-report alone and on “corrected” report in which cases detecting positive after not reporting use were coded as use. It should be noted that not testing positive after reporting use was not considered when correcting self-reporting as overreporting (e.g., mischievous reporting) has been shown to be more of an adolescent phenomenon (34, 35). Further, shorter hair samples represent smaller timeframes of detection. Since our aim was to estimate prevalence to the nightclub and festival-attending population rather than to merely describe prevalence within the sample, we created and used sample weights when examining these trends (36). As such, selection probabilities were computed based on reported frequency of nightclub/festival attendance and response rate for each night of recruitment. Weights for frequency of attendance were inversely proportional to attendance frequency and weights were inversely proportional to event-level response rates. The two weight components were combined via multiplication and normalized. These probability weights were accounted for differential selection probability and clustering of participants entering each event. Using these weights, we estimated prevalence based on self-report and then on corrected report for each year, and then estimated trends based on the trend analysis methods previously described. Analyses were conducted using Stata SE 17.

Results

The majority of participants were male (55.0%), and the plurality was white (48.6%), with 328 (16.8%) providing an analyzable hair sample (Table 1). There were significant differences with respect to race/ethnicity (p=.030) and sexual orientation (p=.002) regarding who provided an analyzable hair sample with posthoc tests suggesting black and gay/lesbian participants were less likely to provide an analyzable sample.

With respect to drug positivity, overall, the majority of participants tested positive for cocaine exposure (55.2%), and this was followed by exposure to ketamine (37.2%), MDMA (33.8%), amphetamine (13.7%), methamphetamine (7.0%), and MDA (4.9%) (Table 2). With regard to discordant reporting, which was defined as testing positive for exposure after not reporting use, cocaine was the most underreported drug (37.1%), followed by ketamine (26.4%), and ecstasy/MDMA (11.8%). When using hair test results to ‘correct’ self-report, prevalence of use of cocaine and ketamine each increased by 19.8%. Prevalence of use of MDMA, amphetamine, and methamphetamine increased 6-7% when considering positive test results as use. With regard to other drugs (Table 2 continued), cannabis was the most prevalent drug self-reported and hair testing only added 0.9% when correcting prevalence. Reported use of psychedelics (particularly LSD) was under-detected by hair testing. There was typically some underreporting of less common drugs but using hair test results to correct prevalence rarely added more than 2% to prevalence. Of note, prescription opioid exposure was underreported by 7.9% of those testing positive, and there were some cases of underreported exposure to fentanyl or its analogs (n=3), eutylone (n=5), and a synthetic cannabinoid (BZO-4en-POXIZID) (n=5).

Between 2019 and 2022 (Table 3 and Figure 1), prevalence of positivity decreased for cocaine, ketamine, MDMA, and amphetamine (ps<.05), with particular decreases after the onset of COVID (ps<.01). MDA detection also decreased to 0% but a statistical comparison between 2019 and 2022 could not be conducted. The largest decreases in positivity were for MDA (a 100.0% decrease) and amphetamine (a 74.7% decrease). Between 2019 and 2022, MDA underreporting reduced to 0%, and underreporting of use of ketamine and cocaine decreased by 81.6% and 39.6%, respectively (ps<.05).

Table 4 presents comparisons regarding who reported past-year use vs. those who did not with regard to any detection and level of detection (among positive cases). In multivariable models, any detection was significantly more prevalent among those reporting past-year use of ecstasy/MDMA (aPR=5.20, 95% CI: 3.22-8.39), amphetamine (aPR=3.63, 95% CI: 1.96-6.72), ketamine (aPR=2.75, 95% CI: 1.89-4.00), and cocaine (aPR=1.91, 95% CI: 1.39-2.61). Detection of methamphetamine was higher among those reporting use in the bivariable model but not the multivariable model. Regarding level of detection (among cases testing positive), higher levels were detected for methamphetamine (b=92.07, SE=77.70, p<.001), ketamine (b=13.95, SE=4.54, p<.001), cocaine (b=3.05, SE=1.11, p=.002), and MDMA (b= 3.07, SE=1.20, p=.004) among those reporting use both in bivariable and in multivariable models.

Given that cocaine and ketamine were the most underreported drugs, we delineated correlates of underreported use (Table 5). Prevalence of discordant report of cocaine use was higher post-COVID (aPR=1.88, 95% CI: 1.07-3.32) and among those surveyed entering a festival (vs. a nightclub; aPR=2.26, 95% CI: 1.12-4.59), and lower among those reporting past-year use of ecstasy (aPR=0.52, 95% CI: 0.28-0.99) or cocaine (aPR=0.17, 95% CI: 0.07-0.46). Prevalence of discordant report of ketamine use was lower post-COVID (aPR=0.37, 95% CI: 0.15-0.87) and among those reporting past-year cocaine use (aPR=0.56, 95% CI: 0.33-0.95), and prevalence was higher among females (aPR=1.78, 95% CI: 1.01-3.12). Prevalence of discord was lower among those testing positive for MDMA in the bivariable model (56.9% vs. 75.4% testing negative; p=.032), but significance did not hold in the multivariable model.

Finally, trends in use (between 2019 and 2022) were estimated (using weighted data) based on self-report and then based on corrected self-report in which those testing positive for exposure after not reporting use were coded as having used (Table 6 and Figure 2). Both self-reported prevalence and prevalence of corrected report significantly decreased for cocaine and ecstasy use, with larger decreases in corrected report. Specifically, self-reported cocaine use decreased by 34.4% and corrected report decreased by 38.4%; self-reported ecstasy/MDMA use decreased by 21.5% and corrected report decreased by 26.9% (ps<.05).

Discussion

Individuals in this population reporting use of a wide variety of drugs, especially common party drugs, and estimated prevalence of use tended to be higher when incorporating hair test results. Results suggest that a combination of self-report and biospecimen testing tends to better inform prevalence of use that either alone.

Discordant report was most common regarding cocaine and ketamine use with hair test results adding nearly 20% to past-year prevalence of each via our correction. It is unknown to what extent known use was intentionally underreported or whether exposure was due to one of these drugs being present in another drug such as ecstasy, which historically has been adulterated with a wide range of drugs (6, 7). It is also possible that some unknown exposure to ketamine was via the new powder concoction called Tusi, which is gaining popularity in the US and almost always contains ketamine (37). Since reported use was often associated with higher levels of detection, it may be that those not reporting use but testing positive tended to be unknowingly exposed. There may also have been cases in which a participant tried a drug and did not feel it was significant enough to report. It is noteworthy that positivity and discordant report of use of these two drugs decreased over time. Given that the survey did not change, it seems more likely that participants were unknowingly exposed. We also detected some cases of underreported use of synthetic cannabinoids, fentanyl, and ethylone. It is possible that ethylone in particular was present in ecstasy, as unintentional use of synthetic cathinones, historically, has tended to be linked to ecstasy use (11, 12). A larger concern was possible unknown exposure to fentanyl, and in NYC, it is possible that this compound was present in cocaine (38).

Positivity of most of the main drugs of focus (i.e., cocaine, ketamine, MDMA, MDA, amphetamine) decreased across time, particularly post-COVID. Estimates of use of cocaine and MDMA also decreased over time, particularly after the onset of COVID. Although, discordant report of cocaine use increased after COVID, and discordant report of ketamine use decreased after COVID. Recent estimates from other studies also suggest that suggest that use of drugs such as ecstasy declined during the pandemic and that prevalence has not rebounded (2, 17, 39). Results may suggest shifts in purity of these drugs, but more research is needed.

Finally, with respect to correlates of discordant reporting of cocaine and ketamine use, self-reported use of other prevalent party drugs was often associated with lower prevalence of discordant report, suggesting that (known) experience with other drugs was possibly protective against possible unknown exposure. A previous study of this population also found that use of more drugs was associated with lower risk of discordant report (13). In addition, females were more likely to underreport ketamine exposure and those recruited at festivals (as opposed to nightclubs) had a higher prevalence of underreported cocaine exposure. This adds to previous studies which suggest that festival attendees may be at higher risk that nightclub attendees, possibly due to a lack of drug-taking experience or risky drug purchasing practices (40).

Limitations

Only a portion of those surveyed provided (analyzable) hair samples which can bias results. Although, analysis of a larger portion of hair samples in large-scale survey epidemiology studies is expensive and not always feasible, which is why some other large studies have opted to analyze only a small portion (e.g., <10%) of samples collected (41). We also detected differential submission rates with black and gay/lesbian-identifying individuals less likely to provide analyzable samples which can further bias results. While 12 cm of hair corresponds to roughly a one-year timeframe, shorter samples can not cover a full year. As such, drug positivity could not always be detected, particularly when shorter hair was provided. We did control for hair length in models when possible, however. Further, hair testing is not the most efficacious in detecting THC use (especially infrequent use) and psychedelics such as LSD can be very difficult to detect in biospecimens (23-25, 42, 43). External contamination was also possible in some cases, especially given that for most drugs we considered trace amounts as positive (33), but we believe considering small amounts positive is important considering unknown exposure to small amounts as adulterants is possible, especially in this population. Further, given that MDA is a metabolite of MDMA, we relied on a conservative ratio (of MDA/MDMA ≥0.2) to indicate external exposure as opposed to detection of MDA as a mere metabolite of MDMA use.

Conclusion

Underreporting of use of drug use was common in this high-risk population and suggests the need for researchers to better deduce intentional underreporting vs. unknown drug exposure via adulterants. Researchers should consider both self-report and toxicology results when estimating trends in drug use.

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