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CLINICAL RESEARCH

Trends and correlates of discordant reporting 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 products is common. We examined the prevalence of drug use in this population, based both on self-reporting and on hair test results, with a focus on the detection of underreported use.

Methods: Adults 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 reporting).

Results: Of the 328 who provided a sample, cocaine and ketamine were the most frequently detected drugs (55.2% [$n = 181$] and 37.2% [$n = 122$], respectively), but these were also the two most underreported drugs, with 37.1% ($n = 65$) and 26.4% ($n = 65$), respectively, testing positive after not reporting use. Between 2019 and 2022, positivity decreased for cocaine, ketamine, 3,4-methylenedioxymetamfetamine, and amfetamine, and underreported exposure to cocaine and ketamine also decreased ($P < 0.05$). Underreporting of the use of these drugs was common, but we also detected underreported exposure to ethylone, fentanyl, 3,4-methylenedioxyamfetamine, metamfetamine, and synthetic cannabinoids. Prevalence of discordant reporting of cocaine use was higher among those testing positive for ketamine exposure (adjusted prevalence ratio = 2.63; 95% CI: 1.48–4.69) and prevalence of discordant reporting of ketamine use was lower post-coronavirus disease caused by the SARS-CoV-2 virus (adjusted prevalence ratio = 0.39; 95% CI: 0.16–0.91) and among those reporting cocaine use (adjusted prevalence ratio = 0.53; 95% CI: 0.32–0.89).

Discussion: Underreporting of drug use was common, suggesting the need for researchers to better deduce intentional underreporting versus unknown drug exposure *via* adulterants.

Conclusions: Researchers should consider both self-report and toxicology results from biological samples when examining trends in use.

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Introduction

Evidence regarding the prevalence of drug use is important in informing prevention, treatment, and harm reduction efforts. The main method used to estimate the prevalence of drug use is self-report (e.g., *via* surveys). For example, national drug surveys are the main source for estimating trends in the incidence and prevalence of drug use [1,2]. However, underreporting of drug use is common as survey responders may fear disclosing their use; 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 3,4-methylinedioxymetamfetamine (MDMA) and heroin, historically, tend to be adulterated or replaced with other substances, so it is also common for people who use to have been unknowingly exposed to drugs they did not intend to consume [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 patterns of exposure [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 the use of common party drugs such as MDMA, cocaine, and ketamine [17–19], but this population is also at high risk for being unknowingly exposed to adulterants, contaminants, and replacement drugs, including new psychoactive

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substances [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.

The main objective of this study was to determine the prevalence of drug use in this population, based both on self-reporting and on hair test results, with a particular focus on detection of underreported use or exposure. Related to this objective, prevalence was examined in a cross-sectional manner (using data from aggregated years) and repeated cross-sectional data (examining trends by year). In this analysis, we focused on the use of a wide variety of drugs with a particular focus on six of the most common drugs used in the nightlife-attending population—cocaine, MDMA, ketamine, amfetamine, metamfetamine, and 3,4-methylinedioxyamfetamine (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 analyses were compared. In hair samples, the aforementioned substances are easily detected, unlike, for example, lysergic acid diethylamide [23–25]. Further, since a particular concern is exposure to drugs that are adulterated, contaminated or even outright replaced with other drugs, the presence of the substances above the limits of detection was used to identify positive samples rather than standard cutoffs [26]. 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 party ticket website and also based on recommendations from key informants [17]. Individuals were eligible if they were age $\geq$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 also asked if they were willing to provide a hair sample for future analysis. Those completing the survey were compensated $10 US, and those providing a hair sample were offered an additional $5 US. Hair samples were cut using a clean scissor and were folded into small sheets of tin foil, which were sealed in separate envelopes labeled with participant study identification (ID) numbers. Hair samples were then stored in a locked drawer at room temperature until shipped to the toxicology lab for analysis. 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 electronic dance music event attendance in the past year. Participants were also asked about past-year use of drugs, including cocaine, MDMA (Ecstasy, Molly), ketamine, amfetamine (nonmedical use), metamfetamine, and MDA. Molly was added to the definition of MDMA as this is a common name for this drug in the United States (US) [27]. A list of drugs queried on the survey is presented in Table S1.

Hair analysis

Hair samples were tested *via* published methods using ultra-high performance liquid chromatography–tandem mass spectrometry (UHPLC-MS/MS) [28, 29]. A full list of targeted analytes is presented in Table S2. 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 new psychoactive substances not in our library [30]. Before analysis, samples were decontaminated by an initial wash with dichloromethane 1 mL, followed by a second wash with methanol 1 mL. In this analysis, we focused primarily on the detection of cocaine, MDMA, ketamine, amfetamine, metamfetamine, and MDA, as these were among the most common drugs detected, allowing for trend analyses. Given that exposure to drugs that were adulterated, contaminated, or replaced with other drugs was of interest, we set the limits of detection as the minimum criterion to identify positive samples. The exception was MDA. 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 $\geq$0.2 [31,32]. Hair samples were analyzed in their full length up to 12 cm, representing up to a 12-month timeframe [33]. Samples had to weigh at least 20 mg in order to be considered large enough for analysis.

Statistical analyses

First, we calculated descriptive statistics to describe the study sample, and we used chi-square and independent samples t-tests to determine whether there were differences in sample characteristics according to whether an analyzable hair sample was provided.

Then, focusing on those who provided an analyzable hair sample, we calculated

1. the prevalence of past-year drug use based on self-reporting;
2. the prevalence of drug positivity;
3. the prevalence of discordant reporting (defined as testing positive after not reporting use);
4. the "corrected" prevalence (in which cases testing positive after not reporting use were coded as use);

5. what hair testing added to self-reporting. This was calculated by subtracting the prevalence based on self-reporting from the corrected prevalence.

It should be noted that not testing positive after reporting use was not considered when correcting self-reporting as overreporting; mischievous reporting (typically over-reporting) is more of an adolescent phenomenon [34,35]. We computed these statistics for all drugs detected.

Next, we examined trends in positivity and discordant reporting between 2019 and 2022 by year for the six main drugs of interest—cocaine, ketamine, MDMA, MDA, amfetamine, and metamfetamine. 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-coronavirus disease caused by the SARS-CoV-2 virus (COVID-19) 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).

We then determined how self-reported use of the main six drugs of interest was related to 1) *any* detection (yes/no) and 2) the *level* of detection of that drug. Regarding any detection, we determined whether there were bivariable differences in detection versus 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 using Poisson and log-link, which generated an adjusted prevalence ratio for use in relation to any positive detection. For level of detection (among positive cases), we first compared the 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 generalized linear models (using a gamma distribution and log-link) with robust standard errors. All of these multivariable models were controlled for year, participant sex, age, race/ethnicity, sexual orientation, type of venue where recruited, and hair length.

Next, in a supplemental analysis, we delineated correlates of discordant reporting of cocaine and ketamine use. As such, first we tested for differences between each covariate of interest and whether there was discordant reporting using chi-square and independent samples t-test, and then hair length and all other covariates that were significant at the bivariable level were fit into multivariable generalized linear models using Poisson and log-link.

Finally, we estimated trends in the prevalence of use of each of the main six drugs of interest in the population based on 1) self-reporting alone and on 2) "corrected" report. Since our aim was to estimate prevalence in the nightclub and festival-attending population rather than to merely describe prevalence within the sample, we created and used sample weights when estimating these trends [36]. As such, selection probabilities were computed based on the 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 accounted for differential selection probability and clustering of participants entering each event. Using these weights, we estimated prevalence based on self-reporting 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

Participants were surveyed entering 115 events, and the overall survey response rate was 69%. Of the 1,953 participants surveyed, a quarter (24.9%, $n = 486$) provided a hair sample, and 328 samples were large enough to analyze (67.5% of those submitted and 16.8% of the full sample). Of those providing an analyzable sample, the majority were male (52.4%, $n = 172$), white (51.8%, $n = 170$), and heterosexual (69.8%, $n = 229$) (Table 1). When comparing those who provided an analyzable sample to those who did not, there were significant differences with respect to race/ethnicity ($P = 0.030$) and sexual orientation ($P = 0.002$), with post hoc tests suggesting black and gay/lesbian participants were less likely to provide an analyzable sample.

Among those who provided an analyzable hair sample ($n = 328$), with respect to drug positivity, overall, the majority of participants tested positive for cocaine exposure (55.2%, $n = 181$), and this was followed by exposure to ketamine (37.2%, $n = 122$), MDMA (33.8%, $n = 111$), amfetamine (13.7%, $n = 45$), metamfetamine (7.0%, $n = 23$), and MDA (4.9%, $n = 16$) (Table 2). With regard to discordant reporting, which

Table 1. Demographic characteristics of the sample ($n = 1953$).

		Provided an analyzable hair sample			
		Column percentages		Row percentages	
	Full sample *n* (%)	No *n* (%)	Yes, *n* (%)	No, %	Yes, %
Time period					
Pre-COVID-19	1,109 (56.8)	911 (56.1)	198 (60.4)	82.2	17.9
Post-COVID-19	844 (43.2)	714 (43.9)	130 (39.6)	84.6	15.4
Age (mean ± SD)	26.7 ± 6.0	26.8 ± 6.0	26.1 ± 5.9	–	–
Sex					
Male	1,075 (55.0)	903 (55.6)	172 (52.4)	84.0	16.0
Female	878 (45.0)	722 (44.4)	156 (47.6)	82.2	17.8
Race/ethnicity					
White	949 (48.6)	779 (47.9)	170 (51.8)[a]	82.1	17.9
Black	159 (8.1)	144 (8.9)	15 (4.6)	90.6	9.4
Hispanic	377 (19.3)	307 (18.9)	70 (21.3)	81.4	18.6
Asian	289 (14.8)	250 (15.4)	39 (11.9)	86.5	13.5
Other/mixed	179 (9.2)	145 (8.9)	34 (10.4)	81.0	19.0
Sexual orientation					
Heterosexual	1,323 (67.7)	1,094 (67.3)	229 (69.8)	82.7	17.3
Gay/lesbian	278 (14.2)	250 (15.4)	28 (8.5)	89.9	1.1
Bisexual/other	352 (18.0)	281 (17.3)	71 (21.7)[b]	79.8	20.2
Recruitment venue					
Nightclub	1,693 (86.7)	1,403 (86.3)	290 (88.4)	82.9	17.1
Festival	260 (13.3)	222 (13.7)	38 (11.6)	85.4	14.6

Note. A total of 328 analyzable hair samples were provided (16.8% of the full sample). Pre-COVID-19 = 2019 and early 2020; Post-COVID-19 = 2021 and 2022; SD: standard deviation.
[a]$P < 0.05$, [b]$P < 0.01$.

Table 2. Drugs reportedly used compared to drugs detected among those providing an analyzable hair sample ($n = 328$), 2019–2022.

	Reported use *n* (%)	Hair positive *n* (%)	Discordant reporting n^1/n^2 (%)	Corrected prevalence *n* (%)	What hair testing adds to self-report %
Cocaine	153 (46.7)	181 (55.2)	65/175 (37.1)	218 (66.5)	19.8
3,4-Methylenedioxymetamfetamine	141 (43.0)	111 (33.8)	22/187 (11.8)	163 (49.7)	6.7
Ketamine	82 (25.0)	122 (37.2)	65/246 (26.4)	147 (44.8)	19.8
Amfetamine	81 (24.7)	45 (13.7)	20/247 (8.1)	101 (30.8)	6.1
Metamfetamine	18 (5.5)	23 (7.0)	19/310 (6.1)	37 (11.3)	5.8
3,4-Methylenedioxyamfetamine	20 (6.1)	16 (4.9)	11/308 (3.6)	31 (9.5)	3.4
Other drugs	Reported use *n* (%)	Hair positive *n* (%)	Discordant reporting n^1/n^2 (%)	Corrected prevalence *n* (%)	What hair testing adds to self-report %
Cannabis	272 (82.9)	91 (27.7)	3/56 (5.4)	275 (83.8)	0.9
Lysergic acid diethylamide	92 (28.1)	4 (1.2)	0/236 (0.0)	92 (28.1)	0.0
Prescription opioids	19 (5.8)	10 (3.1)	7/309 (2.3)	7 (2.3)	2.1
Hydrocodone	6 (1.8)	6 (1.8)	3/322 (0.9)	9 (2.7)	0.9
Oxycodone	7 (2.1)	3 (0.9)	2/321 (0.6)	9 (2.7)	0.6
Morphine	3 (0.9)	1 (0.3)	1/325 (0.3)	4 (1.2)	0.3
Codeine	10 (3.1)	11 (3.4)	1/318 (0.3)	11 (3.4)	0.3
Methadone	1 (0.3)	1 (0.3)	1/327 (0.3)	2 (0.6)	0.3
Tramadol	5 (1.5)	7 (2.1)	6/323 (1.9)	11 (3.4)	1.8
4-Bromo-2,5-dimethoxyphenethylamine	18 (5.5)	1 (0.3)	0/310 (0.0)	18 (5.5)	0.0
Synthetic cannabinoids	13 (4.0)	5 (1.5)	5/315 (1.6)	18 (5.5)	1.5
N,N-Dimethyltryptamine	10 (3.1)	2 (0.6)	0/318 (0.0)	10 (3.1)	0.0
Phencyclidine	3 (0.9)	1 (0.3)	1/325 (0.3)	4 (1.2)	0.3
3,4-Methylenedioxy-N-ethylamfetamine	2 (0.6)	5 (1.5)	5/326 (1.5)	7 (2.1)	1.5
Heroin	2 (0.6)	1 (0.3)	0/326 (0.0)	2 (0.6)	0.0
Fentanyl or its analogs	2 (0.6)	3 (0.9)	3/326 (0.9)	4 (1.2)	0.3
Ethylone	1 (0.3)	5 (1.5)	5/327 (1.5)	6 (1.8)	1.5

Note. All percentages are unweighted. Reported use refers to self-reported use in the past year. Discordant report refers to the number of cases testing positive among those not reporting use. Fractions represent the number of positive cases out of those not reporting use (n^1/n^2). Positivity was based on any level of the drug detected with one exception: positive 3,4-methylenedioxyamfetamine exposure was estimated as when the ratio of 3,4-methylenedioxyamfetamine /3,4-methylenedioxymetamfetamine $\geq$0.2, which conservatively estimates external exposure rather than 3,4-methylenedioxymetamfetamine metabolization. "What hair testing adds to self-report" is the difference between corrected prevalence and self-reported use.

was defined as testing positive for exposure after not reporting use, cocaine was the most underreported drug (37.1%; 65 testing positive out of 175 not reporting use), followed by ketamine (26.4%; 65 testing positive out of 246 not reporting use), and MDMA (11.8%; 22 testing positive out of 187 not reporting use). When using hair test results to "correct" self-reporting, the prevalence of use of cocaine and ketamine each increased by 19.8%. Prevalence of use of MDMA, amfetamine, and metamfetamine increased by 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 lysergic acid diethylamide) 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 2.3% of those testing positive (seven testing positive out of 309 not reporting nonmedical use), and there were some cases of underreported exposure to fentanyl or its analogs (three testing positive out of 326 not reporting use), eutylone (five testing positive out of 327 not reporting use), and a synthetic cannabinoid (BZO-4en-POXIZID) (five testing positive out of 315 not reporting use).

Between 2019 and 2022 (Table 3 and Figure 1), the prevalence of positivity decreased for cocaine, ketamine, MDMA, and amfetamine ($P < 0.05$), with particular decreases after the onset of COVID-19 ($P < 0.01$). 3,4-Methylenedioxyamfetamine 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 amfetamine (a 74.7% decrease). Between 2019 and 2022, MDA underreporting reduced to 0%, and underreporting of the use of ketamine and cocaine decreased by 81.6% and 39.6%, respectively ($P < 0.05$).

Table 4 presents comparisons regarding who reported past-year use versus those who did not with regard to any detection and level of detection (among positive cases). The small median values coupled with the relatively large means, ranges, and standard deviations suggest (often extreme) positive skewness of distributions. In multivariable models, any detection was significantly more prevalent among those reporting past-year use of MDMA (adjusted prevalence ratio =5.20; 95% CI: 3.22-8.39), amfetamine (adjusted prevalence ratio =3.63; 95% CI: 1.96-6.72), ketamine (adjusted prevalence ratio =2.75; 95% CI: 1.89-4.00), and cocaine (adjusted prevalence ratio =1.91; 95% CI: 1.39-2.61). Detection of metamfetamine was higher among those reporting use in the bivariable model but not the multivariable model. Regarding the level of detection (among cases testing positive), higher levels were detected for metamfetamine (exponentiated coefficient = 92.07; standard error = 77.70; $P < 0.001$), ketamine (exponentiated coefficient =13.95; standard error = 4.54; $P < 0.001$), cocaine (exponentiated coefficient =3.05; standard error =1.11; $P = 0.002$), and MDMA (exponentiated coefficient = 3.07; standard error =1.20; $P = 0.004$) 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 S3). Prevalence of discordant reporting of cocaine use

Table 3. Trends in positive detection and in positive detection after not reporting use (discordant reporting), 2019–2022.

	Prevalence				Trend between 2019 and 2022		
Positive detection	2019 *n* (%)	2022 *n* (%)	Absolute change (%)	Relative change (%)	2022 vs. 2019 adjusted odds ratio (95% CI)	Linear trend adjusted odds ratio (95% CI)	Post- versus Pre-COVID-19 adjusted odds ratio (95% CI)
Cocaine	115 (65.7)	30 (49.2)	−16.5	−25.2	0.45 (0.34–0.86)	1.42 (1.04–1.95)[a]	0.40 (0.24–0.64)
Ketamine	84 (48.0)	13 (21.3)	−26.7	−55.6	0.27 (0.13–0.55)	0.60 (0.48–0.75)	0.28 (0.16–0.47)
3,4-Methylenedioxymetamfetamine	76 (43.4)	13 (21.3)	−22.1	−50.9	0.26 (0.12–0.54)	0.60 (0.48–0.76)	0.31 (0.18–0.53)
Amfetamine	34 (19.4)	3 (4.9)	−14.5	−74.7	0.22 (0.06–0.81)	0.60 (0.42–0.85)	0.31 (0.13–0.73)
Metamfetamine	14 (8.0)	3 (4.9)	−3.1	−38.5	0.72 (0.19–2.79)	0.90 (0.60–1.33)	0.72 (0.27–1.90)
3,4-Methylenedioxyamfetamine	10 (5.7)	0 (0.0)	−5.7	−100.0	—	0.84 (0.53–1.33)	1.04 (0.34–3.18)

	Prevalence				Trend between 2019 and 2022		
Discordant Report	2019 *n* (%)	2022 *n* (%)	Absolute change (%)	Relative change (%)	2022 vs. 2019 adjusted odds ratio (95% CI)	Linear trend adjusted odds ratio (95% CI)	Post- vs. Pre-COVID adjusted odds ratio (95% CI)
Cocaine	40 (50.6)	11 (30.6)	−20.1	−39.6	0.40 (0.16–0.76)	0.69 (0.52–0.90)	0.44 (0.23–0.87)
Ketamine	54 (39.7)	3 (7.3)	−32.4	−81.6	0.11 (0.03–0.39)	0.39 (0.27–0.58)	0.10 (0.04–0.25)
3,4-Methylenedioxymetamfetamine	14 (15.6)	2 (5.7)	−9.9	−63.3	0.23 (0.04–1.22)	0.63 (0.40–1.00)	0.39 (0.12–1.05)
Amfetamine	14 (10.9)	2 (4.1)	−6.8	−62.4	0.45 (0.09–2.28)	0.79 (0.51–1.24)	0.65 (0.22–1.92)
Metamfetamine	11 (6.8)	3 (5.2)	−1.6	−23.4	0.97 (0.24–3.99)	1.01 (0.66–1.53)	0.98 (0.35–2.74)
3,4-Methylenedioxyamfetamine	6 (3.6)	0 (0.0)	−3.6	−100.0	—	0.93 (0.55–1.61)	1.40 (0.37–5.35)

Note. Discordant reporting is defined as testing positive for use after not reporting past-year use. Pre-COVID is defined as 2019-early 2020 and post-COVID is defined as 2021–2022. Positive for 3,4-methylenedioxyamfetamine exposure was estimated as when the ratio of 3,4-methylenedioxyamfetamine/3,4-methylenedioxymetamfetamine ≥0.2, which conservatively estimates external exposure rather than 3,4-methylenedioxymetamfetamine metabolization. "—" indicates that trend test could not be conducted. Bold values indicate a significant trend. [a]Quadratic trend detected. CI: confidence interval.

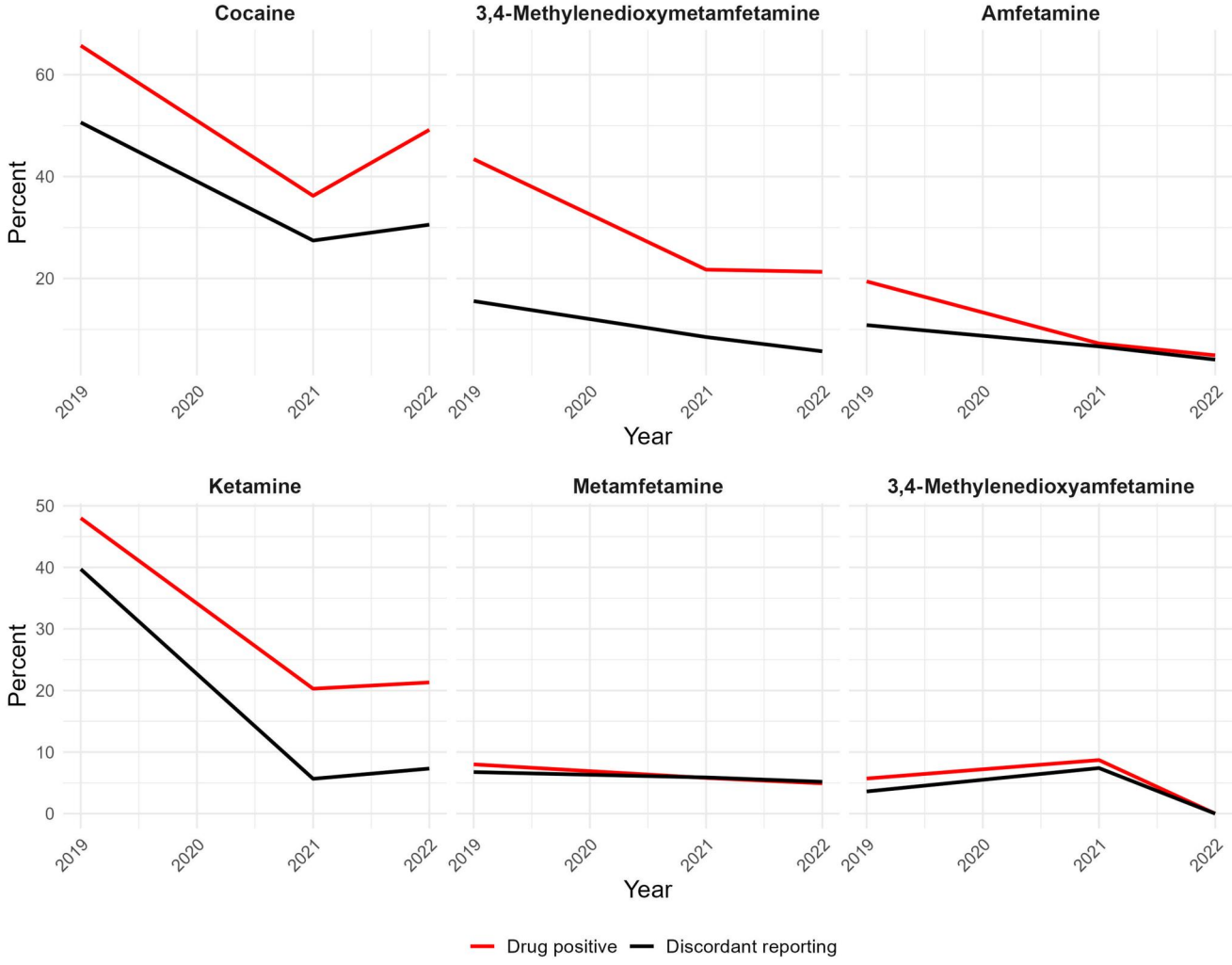

Figure 1. Trends in prevalence of drug positivity and discordant reporting, 2019–2022.

Table 4. Comparisons of any drug detection and level detected according to self-reported past-year use.

	Any detection			Level detected		
Self-reported use	Negative *n* (%)	Positive *n* (%)	Adjusted prevalence ratio (95% confidence interval)	Mean ± standard deviation	Median (range)	Exponentiated coefficient (standard error)
Cocaine						
No	110 (74.8)	65 (35.9)[c]	Reference group	3.6 ± 11.8	0.5 (0.05–80.80)[c]	Reference group
Yes	37 (25.2)	116 (64.1)	1.91 (1.39–2.61)[c]	11.4 ± 32.0	1.4 (0.06–230.00)	3.05 (1.11)[b]
Ketamine						
No	181 (87.7)	65 (53.3)[c]	Reference group	0.5 ± 1.0	0.4 (0.01–4.86)[c]	Reference group
Yes	25 (12.1)	57 (46.7)	2.75 (1.89–4.00)[c]	12.4 ± 42.2	1.4 (0.03–237.00)	13.95 (4.54)[c]
3,4-Methylenedioxymetamfetamine						
No	165 (76.0)	22 (19.8)[a]	Reference group	2.2 ± 3.5	0.5 (0.03–15.30)[c]	Reference group
Yes	52 (24.0)	89 (80.2)	5.20 (3.22–8.39)[c]	7.0 ± 16.3	1.6 (0.06–118.00)	3.07 (1.20)[b]
3,4-Methylenedioxyamfetamine						
No	264 (95.0)	44 (88.0)	Reference group	2.8 ± 10.6	0.1 (0.06–70.81)	Reference group
Yes	14 (5.0)	6 (12.0)	2.24 (0.75–6.65)	1.1 ± 1.6	0.3 (0.04–4.05)	0.54 (0.30)
Amfetamine						
No	227 (80.2)	20 (44.4)[c]	Reference group	1.0 ± 1.7	0.3 (0.03–5.13)	Reference group
Yes	56 (19.8)	25 (55.6)	3.63 (1.96–6.72)[c]	0.7 ± 1.2	0.8 (0.03–4.48)	1.18 (0.49)
Metamfetamine						
No	291 (95.4)	19 (82.6)[a]	Reference group	0.3 ± 0.4	0.2 (0.02–1.90)[b]	Reference group
Yes	14 (4.6)	4 (17.4)	3.00 (0.85–10.53)	15.3 ± 21.1	7.5 (0.56–45.83)	92.07 (77.70)[c]

Note. Self-reported use refers to reported use in the past year. Any detection includes trace detection, and this applies to any concentration of the drug detected, although testing positive for 3,4-methylenedioxyamfetamine exposure was estimated as when the ratio of 3,4-methylenedioxyamfetamine/3,4-methylenedioxymetamfetamine ≥0.2, which conservatively estimates external exposure rather than 3,4-methylenedioxymetamfetamine metabolization. "Level detected" only applies to cases testing positive for exposure. The multivariable models controlled for year, sex, age, race/ethnicity, sexual orientation, type of recruitment venue (nightclub vs. festival), and hair length.
[a]$P < 0.05$,
[b]$P < 0.01$,
[c]$P < 0.001$.

was higher among those testing positive for ketamine exposure (adjusted prevalence ratio = 2.63; 95% CI: 1.48–4.69). Prevalence of discordant reporting of ketamine use was lower post-COVID (adjusted prevalence ratio = 0.39; 95% CI: 0.16–0.91) and among those reporting past-year cocaine use (adjusted prevalence ratio = 0.53; 95% CI: 0.32–0.89). Prevalence of discord was lower among those testing positive for MDMA (56.9% versus 75.4% testing negative; $P = 0.032$) and higher for females in bivariable models (50.8% versus 31.6%; $P = 0.32$), but significance did not hold for either variable in the multivariable model.

Finally, trends in use (between 2019 and 2022) were estimated (using weighted data) based on self-reporting and then based on corrected self-reporting in which those testing positive for exposure after not reporting use were coded as having used (Table S4 and Figure 2). Both self-reported prevalence and prevalence of corrected reporting significantly decreased for cocaine and MDMA use, with larger decreases in corrected reporting. Specifically, self-reported cocaine use decreased by 34.4%, and corrected reporting decreased by 38.4%; self-reported MDMA use decreased by 21.5% and corrected reporting decreased by 26.9% ($P < 0.05$).

Discussion

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

Discordant reporting was most common regarding cocaine and ketamine use, with hair test results adding nearly 20% to the 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 MDMA, which historically has been adulterated or replaced 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 reporting of the 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 MDMA, as unintentional use of synthetic cathinones, historically, has tended to be linked to MDMA use [11,12]. A larger concern was possible unknown exposure to fentanyl, and in New York City, 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, amfetamine) decreased across time,

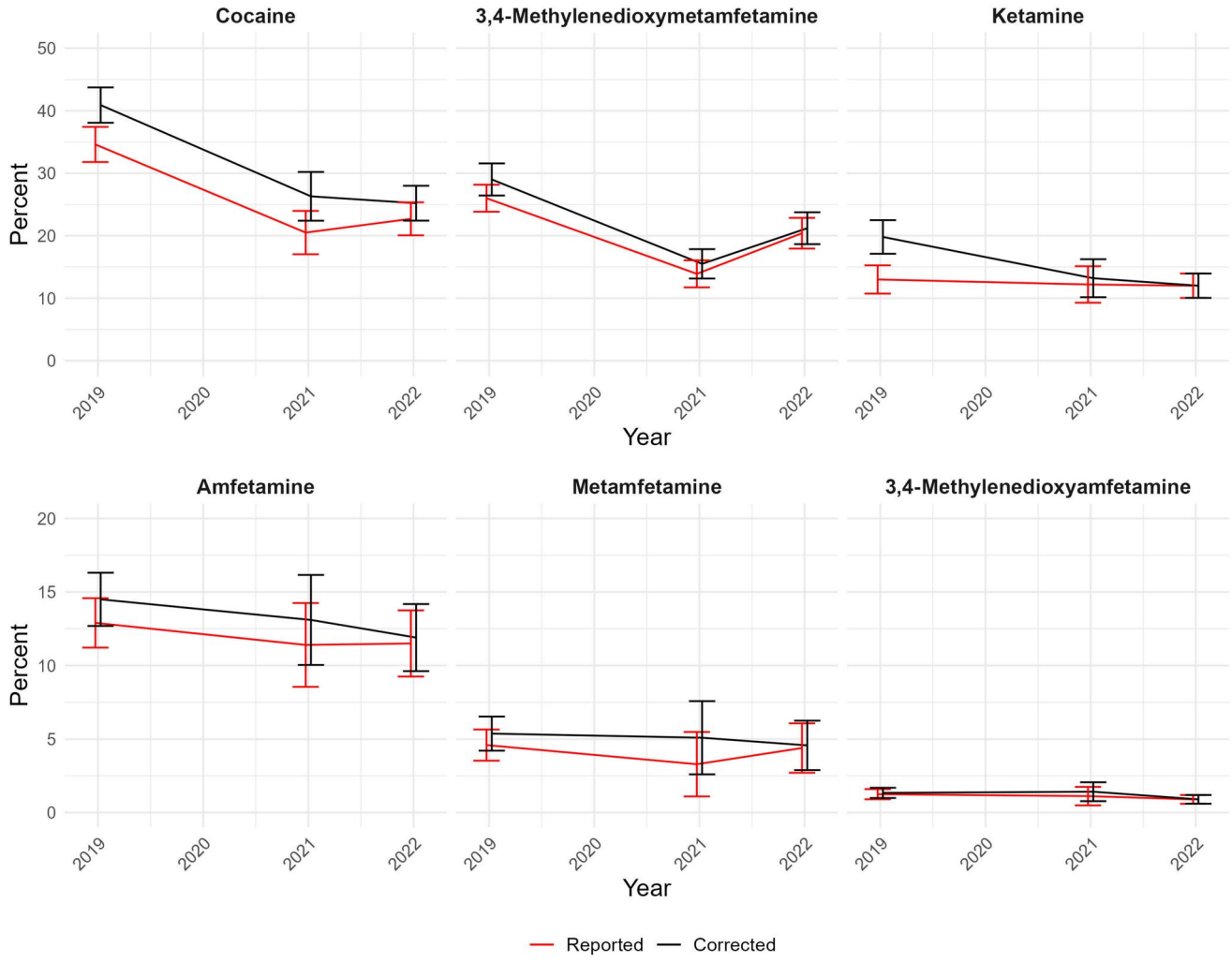

Figure 2. Estimated trends in past-year drug use based on self-reporting and on corrected report.

particularly post-COVID-19. Estimates of use of cocaine and MDMA also decreased over time, particularly after the onset of COVID-19. At the same time, discordant reporting of ketamine and cocaine use decreased after COVID-19. Recent estimates from other studies also suggest that the use of drugs such as MDMA declined during the pandemic and that prevalence has not rebounded [2,17,39]. Results may suggest that the purity of these drugs has been increasing, but more research is needed.

Finally, with respect to correlates of discordant reporting of cocaine and ketamine use, self-reported use of cocaine was associated with a lower prevalence of discordant reporting of ketamine use, and testing positive for ketamine exposure was associated with a higher prevalence of discordant reporting of cocaine use. Associations delineated in this analysis are only correlational, but this result may suggest that (known) experience with other drugs, such as cocaine, may serve as a protective factor against possible unknown ketamine exposure (as more experienced users may be more educated about risks of adulteration), although confirmed ketamine exposure is a risk factor for underreporting cocaine use. A previous study of this population also found that the use of more drugs was associated with a lower risk of discordant reporting [13], but it is possible that unknown cocaine exposure is linked to ketamine exposure. For example, the new drug concoction called "Tusi" commonly contains both ketamine and cocaine [37]. In addition, while a bivariable test suggested that females were more likely to underreport ketamine exposure, this association was no longer significant in the multivariable model (e.g., when controlling for hair length). Although hair length only approached significance in the multivariable model, these findings suggest that hair length is a possible factor with respect to discordant reporting. Further research is needed to investigate this.

Limitations

Only a portion of those surveyed provided (analyzable) hair samples, which can bias results. 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 [40]. 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

cannot cover a full year. As such, drug positivity could not always be detected, particularly when shorter hair was provided. While hair testing is an ideal method for detecting exposure that occurred over a long period of time (ranging from months to possibly years), it is not the most ideal method for detecting use in the past few days. Exposure in the past few days is more easily detected in urine, saliva, and blood [43]. As such, it is possible that very recent exposure was undetected by hair. We did control for hair length in models when possible, however. In addition, hair testing is not the most efficacious in detecting tetrahydrocannabinol use (especially infrequent use), and psychedelics such as lysergic acid diethylamide can be very difficult to detect in biospecimens [23–25,41,42].

It is unknown to what extent unknown exposure occurred (e.g., exposure *via* adulterants or contaminants) vs. intentional underreporting of drug use or even mere forgetting about recent drug use. 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. We believe that detection of even trace amounts of unintentional drug exposure is important in this population, especially as drugs such as fentanyl analogs have begun to adulterate or contaminate party drugs. Further, given that MDA is a metabolite of MDMA, we relied on a conservative ratio (of MDA/MDMA $\geq$0.2) to indicate external exposure as opposed to detection of MDA as a mere metabolite of MDMA use. It should also be noted that demographic and drug use characteristics of participants can affect hair response rates [44], and other factors such as hair treatment (e.g., hair dying) can affect the ability to detect substances in hair [45,46]. Finally, the results of this study may not be fully generalizable to nightclub/festival attendees or to people in New York City who use party drugs. For example, the presence of adulterants in drugs such as MDMA and cocaine tends to vary across regions.

Conclusion

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

Disclosure statement

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