

Identification and assessment of drug-user groups among nightlife attendees: Self-reports, breathalyzer-tests, and oral fluid drug tests

Anne Line Bretteville-Jensen^{*1}, Jasmina Burdzovic Andreas¹, Linn Gjersing¹, Elisabeth Leere Øiestad^{2,3}, Hallvard Gjerde²

¹ Dep. of Alcohol, Tobacco and Drugs, Norwegian Institute of Public Health, Norway

² Dep. of Forensic Sciences, Oslo University Hospital, Norway

³ School of Pharmacy, University of Oslo, Norway

Running head: Identification of drug-user groups among nightlife attendees

Key words: Drug-user groups, person-centered analysis, Latent Class Analysis (LCA), biological drug-tests, BAC levels

*Corresponding author

Anne Line Bretteville-Jensen

Norwegian Institute of Public Health,

Dep. of Alcohol, Tobacco, and Drugs

Post Box 222 Skøyen

0213 Oslo, Norway

anne.line.bretteville-jensen@fhi.no

Phone: +47 98826225

Abstract

Background and objectives: Even though nightlife studies with potentially intoxicated participants provide much needed information on drug use, they face additional methodological challenges. This study aimed to explore the utility of such studies, by i) classifying nightlife attendees based on their self-reported drug use, and ii) examining whether these classifications were meaningful when assessed against other sources of data, including oral fluid drug tests. **Methods:** Self-reported questionnaires, oral fluid samples, and blood alcohol concentration (BAC) readings were collected in a sample of 1,085 nightlife patrons outside 12 popular nightclubs in Oslo, Norway, in 2014. Patrons were classified using multiple approaches, including Latent Class Analysis (LCA). Group differences were examined by logistic regression models. **Results:** Participants were classified into five mutually exclusive groups: two among *current non-users* (“Never-users”; “Previous users”), two among *current users* (“Multiple drugs”; “Cannabis mainly”), and one “Incomplete information” group. Meaningful differences across these groups were observed. For instance, positive tests for any illicit drug were more common in “Multiple drugs” group than in “Cannabis mainly” (62.7% vs. 29.1%, aOR = 3.77 (2.42-5.84)) or “Incomplete information” groups (62.7% vs. 34.4%, aOR = 2.46 (1.26-4.79)). Despite their self-declared non-use, illicit substances were detected in oral fluids of “Never-users” (13.1%; CI 9.9-17.2) and “Previous users” (7.9%; CI 5.1-12.1). **Conclusions:** Despite some discrepancies between self-reports and biological tests, self-reports proved both suitable and useful in identification of substantively different drug-user typologies, potentially informing targeted policy responses. Still, methodological challenges associated with on-site studies of illicit drug use should be further explored.

1. Introduction

Whether for monitoring or research purposes, studies of illegal drug use heavily rely on self-reports. Yet, self-reported data, especially on sensitive topics, are susceptible to a number of known methodological challenges. These range from non-random under- or over-reporting resulting from recall bias, socially desirable responding etc., to missing data on key outcomes (i.e., illegal behaviors like drug use) [1]. While drug tests of biological samples, such as blood, urine, hair, sweat or oral fluids may be useful alternatives to self-reports, they cannot provide crucial information on individual and drug use characteristics of the participants. Furthermore, collection of biological samples may be experienced as both unpleasant and intrusive by the participants, and data collection and analyses are often expensive and demanding. Less intrusive methods such as wastewater analysis provide only aggregate-level data of limited value. Thus, because self-reports are often indispensable for obtaining information on participants' background and drug use history, and in many instances are the only available data source, it is of vital interest and importance to further explore their utility in research on drug use.

Self-reports obtained from general population surveys form the basis for policy-relevant indicators like national prevalence rates. Still, valuable supplements can be obtained from studies directly assessing individuals in settings and situations where high rates of illegal substance use have been documented (e.g., at music festivals, night clubs, etc.). In addition to providing data on drug use in sub-populations of particular interest from a public health perspective, they may further provide in-depth information on use patterns and motives, preferences and risk perceptions, etc.

However, such approaches also bring additional methodological concerns. For instance, face-to-face interviews with potentially intoxicated participants, conducted on-site within the earshot of friends/partners and under limited response time, can add to reporting inaccuracies and missing responses. Missing data issues are common in social science research and can be addressed through a range of statistical approaches under a broad assumption of random missingness [2]. Nevertheless, these assumptions may not be reasonable in situations where randomness is unlikely; i.e., when possibly intoxicated participants are approached in social situations and asked to report on illegal behaviors. Furthermore, non-random missingness may be of particular concern if it involves not a covariate but

sensitive outcomes of interest [3] -- such as illegal drug use. Given the ever-increasing need for accurate and reliable information on illegal drug use, these particular issues, as well as their possible influence on study outcomes, require further exploration.

Studies of drug use in nightlife settings constitute one example of methodologically challenging on-site data collection. Nightlife studies have gained increased attention in recent years as substance use among patrons has been shown to be both common and extensive [4-13]. Still, their drug use is likely to vary greatly. Moreover, such variations may translate into *user groups* characterized by the specific patterns of substance use, socio-demographic and behavioral characteristics, and possibly -- health and social consequences. Even though heterogeneity among nightlife patrons and their substance use behaviors is likely, studies examining these variations remain relatively scarce [14-19]. Better understanding of these individuals, both in terms of numbers and characteristics, may prove informative for a range of tailored policy responses. However, obtaining the much needed individual-level information implies asking the patron directly about their behaviors under less than ideal circumstances (i.e., while intoxicated) and conditions (i.e., on-site). Thus, the unique knowledge and the very purpose of nightlife studies may be compromised by their very characteristics. One way of examining the suitability of self-reports under such research conditions is to examine whether they still adequately capture details and typologies of drug using behaviors, by comparing information obtained from self-reports with equivalent information obtained from other, supplementary sources.

Thus, this research explored the utility of self-reports in studies of illegal drug use involving on-site assessments of potentially intoxicated participants. In addition to questionnaire self-reports, we collected oral fluid samples and blood alcohol concentration (BAC) in a sample of nightlife patrons ($N = 1,085$) recruited outside 12 popular nightclubs in Oslo, Norway. Specifically, we aimed to i) classify nightlife attendees into drug-user groups based upon their self-reported drug use, and ii) examine whether these classifications were meaningful when assessed against other sources of data, including oral fluid drug tests.

2. Data and Method

2.1 Setting

Data were collected in Summer 2014 on Friday and Saturday nights during peak hours (23:00 – 04:00) outside the 12 nightclubs in Oslo, Norway. The premises were selected with the help of an expert group and a set of inclusion criteria such as popularity, opening hours, and geographical spread, specifically to obtain a heterogeneous sample of recreational drug users. Additional details concerning the study design are provided elsewhere [20].

2.2 Data collection procedures

This was a convenience sample and patrons entering and/or exiting targeted venues were approached for anonymous study participation, with 76% ($N = 1,085$) consent rate. Potential participants were informed about the study and if they verbally consented, they were asked to fill out a short paper-and-pencil questionnaire, complete a breathalyzer test, and provide oral fluid samples (i.e., mixed saliva); all three data sources were linked by a common study ID. Free food was offered in lieu of reimbursement. The study was approved by the Regional Committee for Medical and Health Research Ethics in Oslo, Norway (2014/192).

2.3 Measurements

A brief questionnaire collected self-reports on basic demographic-, behavioral-, and substance use characteristics: gender, age, education (\geq college degree), occupational status (employed/ student/ other), and minority background (participant or parents born in Asia or Africa). Participants also reported current smoking status (none/ occasional/ daily smoking during past month), past year visits to alcohol-serving premises after 11pm (\geq 2-3 times per week), alcohol intoxication (\geq 2-3 times a week), and any involvement in physical violence while out drinking (yes/no). Sparse missing cases (max 45 cases for age) were conservatively recoded into the lower risk category or were modeled as a separate group where such recoding was not feasible (gender and age).

Further, participants stated lifetime and past year use of cannabis, amphetamine, ecstasy/MDMA, cocaine, LSD, heroin, GHB, and new psychoactive substances (NPS); and if so, the age of first use. Past year use variables were coded to reflect both a) any use (yes/no), and b) the number

of use occasions (mid-point values for binned response categories). Missing values on drug-related variables were addressed analytically later.

Finally, drug-tests measuring recent substance use were also administered. First, samples of oral fluid (mixed saliva) were collected with the Intercept® Oral Fluid Collection Device (OraSure Technologies Inc., Bethlehem, PA, USA) and analyzed by ultra-high performance liquid chromatography – tandem mass spectrometry [21]. This method is fast, efficient, and less intrusive than blood or urine sampling; it has also been shown to be both valid and reliable in detecting a wide range of substances [22-24]. The participants were classified as positive for “any illicit substance” if tested positive for at least one illicit drug and special attention was also given to positive test results for the two most commonly used drugs: cannabis (THC) and cocaine. Appendix Table A1 documents a complete list of 30 tested illicit substances and corresponding cut-off levels.

Second, current alcohol consumption was measured in terms of Blood Alcohol Concentration (BAC) levels using a breathalyzer (Lion Alcolmeter™ 500 from Lion Laboratories Ltd., Vale of Glamorgan, UK). The instrument readout was an estimated BAC level based on the measured breath alcohol concentration (BrAC). The instrument complies with the EN15964 (2011). The device calculates and displays the BAC level immediately after measurement. A cut-off of 1.2g/L was used to define alcohol intoxication/binge drinking in this study.

2.4 Analyses

Basic descriptive characteristics were reported for all study variables, both for the entire sample and by classified groups. These included relevant parameter estimates (i.e., % or *Mean*) and corresponding 95% confidence intervals (CI) for statistical comparison purposes. Participants with simple and known use histories were manually classified, whereas a Latent Class Analyses (LCA) approach was used to classify current self-reported users of cannabis, cocaine, MDMA/ecstasy, and/or amphetamine based on the past-year use (36). Logistic regression models were used to examine the associations between the identified groups of nightlife attendees and test results from biological samples indicating recent substance use. All analyses, including the LCA-based classification, were conducted in Stata software.

3. Results

3.1 Sample characteristics

Table 1 shows the demographic-, behavioral-, and substance use characteristics for the entire sample. Our participants tended to be young (26.9 ± 6.8), males (63.7%), well educated (63.9% with college degree or greater) and employed or studying (only 6.5% in “other” category). Substance use and related behaviors were common: approximately 1/3 reported current cigarette use and alcohol-related intoxication at least 2-3 times a week. In terms of illicit substance use, 2/3 reported lifetime use of cannabis, and 1/4 and 1/5 reported lifetime cocaine and MDMA/ecstasy use, respectively. The average age of onset was 18.0 (± 3.4). One-fourth (24.7%) tested positive for any illicit substance in oral fluid, while nearly one third (31.9%) had BAC levels equal or greater than 1.2g/L (Table 1).

The past year use of heroin, LSD, GHB, and any new psychoactive substances (NPS) was low, ranging from only 5 cases (0.36%) for heroin to 42 cases (3.87%) for LSD (not shown in Table 1). As a simple validity check, the questionnaire included a non-existent drug “MOP”; only two participants reported having used MOP during the past year. We did not exclude the two users because they had valid drug tests and BAC-readings and therefore represented individuals of substantive interest in this investigation. Both cases had some inconsistencies/missing values on core items, and were accordingly classified into the “Incomplete information” group, please see below for further details of drug-user group classification.

(Table 1 about here)

3.2 Classification of drug-user groups

To classify patrons into drug-user groups we utilized all available information on drug use from self-reports, multiple steps, and general person-centered approaches [25,26]. First, we selected participants with complete (i.e., no missing data) self-reports on key lifetime and current drug-use variables ($n = 1,021$). From those, we identified participants who reported no lifetime use of the key illicit drugs (cannabis, cocaine, amphetamine, MDMA/ecstasy, LSD, heroin, or GHB). Only three in ten reported no such history ($n = 335$) and were accordingly classified into the “Never-user” group.

Next, we identified those participants who reported some drug-use history (i.e., at least one illicit drug used during lifetime), but no current use (i.e., no use of cannabis, cocaine, MDMA/ecstasy, or amphetamine, the four drugs that in this sample showed past year prevalence above 5%). A total of 240 participants were classified into this “Previous user” group. Current users – those reporting past year use of at least one of the four key drugs ($n = 446$) -- were the largest identified group. To detect different patterns, if any, of drug use among these self-reported current users, we used a Latent Class Analysis (LCA) [27].

A two-class LCA solution was selected as the best conceptual and statistical fit (see Appendix A2 for a complete LCA procedure). The first class was characterized by high probabilities of past year cannabis use (posterior probabilities: 99.9% cannabis; 7.9% cocaine; 8.0 % MDMA/ecstasy, and 0.7% amphetamines); consequently, these users were classified into the “Cannabis mainly” group ($n = 288$). The second class was characterized by elevated probabilities of past year use of all drugs but especially of cannabis and cocaine (posterior probabilities: 87.4% cannabis; 85.3% cocaine; 59.9% MDMA/ecstasy, and 39.6% amphetamine), and these users were classified into the “Multiple drugs” group ($n = 158$).

Finally, those participants with incomplete self-reports of drug use ($n = 64$) were not included in the LCA procedures but were classified as a separate “Incomplete information” group and retained for all future analyses as such. Given the nature of data collection procedures, sensitive topic, and missing data on a key outcome reflecting illegal behaviors, we were hesitant to simply assume a random missing mechanism and handle these cases through standard missing-at-random (MAR) techniques [2,3]. Given our study aims, we were also more interested in exploring the information potentially embedded in this group than we were in (possibly erroneously) classifying these participants through LCA. Our selection/classification approaches and the resulting taxonomy are presented in Figure 1.

(Figure 1, about here)

Thus, five mutually exclusive groups of participants were identified: two among *current non-users* (“Never-users” (31%) and “Previous users” (22%)); two among *current users* (“Multiple drugs”

(15%); “Cannabis mainly” (26%)); and finally; “Incomplete information” (6%). To assess whether this classification appeared meaningful, Table 2 shows the relevant estimates and associated 95% CI for basic comparison purposes for the demographic-, behavioral-, and key substance use characteristics across the groups. Of particular interest were putative differences in: a) drug test results indicating recent substance use, and b) self-reports of additional drug-related behaviors. Given that the “Incomplete group” could not be defined in terms of current non-use, and was therefore of substantive interest in this report, it was examined together with *current users* in all subsequent analyses.

(Table 2 about here)

There was a relatively high congruence between our classification and oral fluid test results. As would be expected under conditions of accurate self-reports, the proportion of positive oral fluid tests was in general the greatest in the “Multiple drugs” group. For example, the proportions of positive oral fluid samples for any illegal substance (62.7%) and cocaine (44.7%) were significantly greater in this group than in any of the remaining four groups. While the “Incomplete information” group had a lower proportion of positive tests than the “Multiple drugs” group, it showed many similarities with the “Cannabis mainly” group. However, this was the only group where more than half of the members presented BAC levels $\geq 1.2\text{g/L}$ indicative of alcohol intoxication.

Even though the proportions of positive oral fluid tests were lower in the “Never user” and “Previous user” groups than in the three remaining groups, they were not zero as would have been expected based solely on the self-reports. Specifically, among those who stated no lifetime history whatsoever of illegal drug use, 13.1% tested positive for any drug; 8.4% tested positive for cocaine, and 3.9% tested positive for cannabis (THC) in oral fluid tests. Similar results indicative of some recent drug use were observed among “Previous users” (see Table 2, bottom).

Additional self-reported information (not employed in the LCA) also generally showed an ordered relation, such that the three groups of putative current drug users, and “Multiple drugs” group in particular, were associated with greater likelihoods of self-reported drug involvement and risk behaviors than the two groups of self-declared current non-users. For example, the proportions reporting

smoking, visiting licensed premises, alcohol intoxication, and involvement in physical violence was in general greater among participants classified into “Cannabis mainly”, “Multiple drugs” and “Incomplete information” groups (see Table 2). Differentiation was also observed across the groups of self-declared drug users. For example, frequency of drug use was elevated in the “Multiple drugs” group, such that even past year cannabis use was actually more frequent in this than in the “Cannabis mainly” group. In addition, participants who were classified into the “Multiple drugs” group initiated drug use on average more than a year earlier than those in the “Cannabis mainly” group and more than two and a half years earlier than those in the “Previous users” group .

3.3 Drug-user groups vs. positive oral fluid tests results and BAC levels

To further examine the association between classified drug-user groups and drug-test results, Table 3 presents the results from four logistic regression models: 1) positive oral fluid test results for any illicit substance, 2) positive oral fluid test results for cannabis (THC), 3) positive oral fluid test results for cocaine, and 4) BAC-levels equal or above 1.2g/L.

(Table 3 about here)

Overall, we observed an ordered association similar to the one from Table 2 where the three putative groups of drug users -- and “Multiple drugs” especially -- had greater likelihood of positive tests than the two groups of current non-users. This expected ordering was replicated even within the three putative user groups, such that positive tests for any illicit substance and for cocaine were more likely in the “Multiple drugs” group than either in “Cannabis mainly” [$AOR_{Any_drug} = 3.77 (2.42 - 5.84)$; $aOR_{Cocaine} = 6.56 (3.89 - 11.05)$ for cocaine] or “Incomplete information” groups [$aOR_{Any_drug} = 2.46 (1.26 - 4.79)$; $aOR_{Cocaine} = 3.50 (1.58 - 7.73)$], see footnote of Table 3.

4. Discussion

We have explored the utility of self-reports in on-site studies investigating illegal substance use involving potentially intoxicated participants. Even though such studies are invaluable for obtaining

detailed information required for targeted prevention, harm-reduction, and treatment interventions, they pose additional methodological and ethical challenges in need of further investigation. To this end, we first classified nightlife patrons based on their self-reports using multiple classification steps and all available cases. Next, we explored to what extent this classification proved meaningful when evaluated against additional substance use indicators concurrently obtained from measures of blood alcohol concentration (BAC), oral fluid samples and additional self-reported information.

More precisely, we classified the nightlife attendees into five mutually exclusive groups, namely two among *current non-users* (“Never-users” and “Previous users”); two among *current users* (“Multiple drugs”; “Cannabis mainly”); and one “Incomplete information” group. Our approach utilized commonly used methods such as the LCA to classify drug users, but we were neither solely focused on these statistical approaches nor limited by them. Further, we retained participants with incomplete self-report data and examined them as a group in its own right; this simple classification approach not only provided information frequently neglected in past studies [16,17], but we believe it illuminated some issues of particular concern in studies of this nature. This set of results demonstrates that brief self-reports, their possible shortcomings notwithstanding, were useful in providing a fairly specific information on drug use patterns above and beyond the simple “user vs. non-user” dichotomy.

Our second aim indirectly explored the value of these self-reported data, as the validity of self-reported information in drug use settings has been questioned [5,28-30]. Some have observed poor agreement between oral fluid tests and self-reported drug use [5,28-31], while others reported relatively good validity when examined self-reports against blood, urine, hair or saliva drug tests [32-35]. Even though we did not have direct validation hypotheses, our results suggest that questionnaires still provided information useful for both research and policy purposes. That is, the classified groups aligned in a meaningful manner when tested against other substance use indicators. The fact that the two clearly identified groups of users were associated with greater likelihoods of self-reported risk behaviors and drug involvement than the groups of non-users and “Incomplete Information” group testifies to the utility of self-reported data in this type of studies. In addition, the meaningful ordering was observed even when we omit current non-users, such that “Multiple drugs” users tended to be associated with greater drug involvement than the remaining two groups.

For example, the “Multiple drugs” group individuals were not only defined by extensive polydrug use, but they tended to use more frequently and to have initiated use when younger. They were also up to 6.5 times more likely to test positive for any illicit substance in oral fluid than “Never users”, and they tested positive for any illicit substance (63%) and cocaine (45%) in significantly greater proportion than the remaining groups. In this respect, the “Multiple drugs” group emerged as the likely priority for targeted intervention. This is not to say that “Cannabis mainly” and “Incomplete information” groups were not necessarily at risk for potentially adverse consequences, especially when compared with current non-users. Roughly one third of the “Cannabis mainly” (29.1%) and “Incomplete information” (34.4%) groups still tested positive for any illicit substance, indicating recent drug use. Finally, more than half (54.7%) of the “Incomplete information” group had high BAC levels ($\geq 1.2\text{g/L}$); the only group in our sample which exceeded the 50% mark. It is conceivable that this extensive drug, and especially alcohol, use contributed to impaired comprehension and motor coordination, and ultimately to questionnaire non-completion among the participants from this group [36,37].

The congruence between the self-reported questionnaire and non-questionnaire data sources seemed, however, better for current users than for the current non-user groups. Current non-users were divided between those who reported no lifetime use of any illicit drugs and those who reported no such use in the past year only. Contrary to their negative responses to the questions of current drug use, oral fluid tests revealed non-negligible levels of recent drug use in these two groups as well (13.1% and 7.9% positive for any illicit substance). Even though the reasons for this set of results cannot be ascertained from our data, these evident trends of at least some use among these self-reported non-users suggest that such groups should not be automatically excluded from targeted prevention and harm-reduction interventions. The entirety of our results thus implies that accuracy of self-reports may be more of an issue among those not reporting current drug use than among those who do. Nevertheless, questionnaires remain an important source of information, and for situations where utilization of bio-analytical measures is not possible or desirable they seem to provide meaningful data for person-centered analyses.

Finally, we argue that our results illuminate important methodological and ethical considerations more broadly defined. First, the results from our “Incomplete information” group is consistent with the argument of non-random missingness in studies of sensitive topics such as illicit

drug use. Excluding this group from analyses, or modeling these participants under the missing-at-random assumption may have biased the results. Interestingly, a considerable degree of information was embedded in this “incompleteness”, including the understanding that those participants may have been too intoxicated for coherent study completion, ultimately leading to a systematic pattern of missing data.

Second, the balance between ethical standards (i.e., are intoxicated participants fully capable of consent?) and scientific criteria (i.e., are too strict inclusion rules leading to biased results?) seems rather precarious in studies specifically aiming to detect extensive substance use behaviors. These questions are particularly challenging as the inclusion decisions based only on face-to-face interactions may be unreliable, and as the “objective” levels of intoxication are determined only following the questionnaire completion.

Further, despite the value of self-reports and person-centered approaches in identifying putative groups of drug-users in this study, under-reporting was apparent as roughly one in ten of the stated non-users in our sample tested positive for illegal substances. These figures are non-negligible, even if we attribute some of these cases to unlikely false positives. The fact that about 90 per cent of the participants were under the influence of alcohol and/or illegal substances may have influenced their responses. Furthermore, concerns about sufficient confidentiality or the specific study setting -- where participants were approached in person in public spaces, often in groups of friends -- may also have contributed to social desirability biases. Irrespective of what the causes might have been however, the revealed degree of underreporting implies underestimates of current drug use.

4.1 Strengths and limitations

This study examined a large, heterogeneous sample of nightlife attendees. It utilized detailed self-reports and biological samples (oral fluid and breathalyzer tests), demonstrating both feasibility and utility of combining such approaches in a single study. Even though we did not directly address validation hypotheses, these results suggest the value of self-reported data even among populations with currently high levels of substance use. Our broad person-centered classification approaches and inclusion algorithms resulted in a more nuanced delineation of putative groups of drug users, possibly contributing to corresponding intervention strategies. Nevertheless, this was a convenience sample and

the results are therefore not necessarily generalizable to other nightlife attendees, let alone general populations. In addition, the usual limitations of self-reports remain, together with the more specific concerns discussed above.

4.2 Conclusion

We classified nightlife attendees into five drug-user groups based on their self-reported drug use histories; these classifications aligned in a meaningful manner with the oral fluid tests, BAC levels, and additional self-reported information. Despite some under-reporting, self-reports still provided a suitable basis for meaningful classification, while drug-tests provided a valuable and uniquely informative supplement. Such nuanced classification can in turn be informative for development and implementation of tailored policy strategies.

Acknowledgements: The authors want to thank Håvard Furuhaugen for validating the analytical method for drugs in oral fluid, for managing the drug analyses, and for excellent laboratory work.

Statement of Ethics: The research was conducted in accordance to ethical standards and approved by the Regional Committee for Medical and Health Research Ethics in Oslo, Norway (2014/192).

Disclosure Statement: The authors have no conflicts of interest to declare.

Role of the funding source: This research was funded by The Norwegian Institute of Public Health with financial support from The Norwegian Health Directorate, Oslo University Hospital and University of Oslo. The funding sources had no involvement in study design; in the collection, analysis and interpretation of data; in the writing of the report; or in the decision to submit the article for publication.

Contributions: Anne Line Bretteville-Jensen initiated the study, participated in the team developing the questionnaire, cleaned and analyzed the data, wrote the first draft and finalized the manuscript. Jasmina Burdzovic Andreas analyzed the data, wrote parts of the manuscript and revised the manuscript critically for intellectual content. Linn Gjersing participated in the interpretation of the data and revised the manuscript critically for intellectual content. Elisabeth Leere Øiestad and Hallvard Gjerdre were part of the research team planning the study, contributed to analysis of the oral fluid samples and interpretation of all results. All authors read and approved the final manuscript.

References

- 1 Harrison L, Hughes A: Introduction--the validity of self-reported drug use: improving the accuracy of survey estimates. NIDA research monograph 1997;167:1-16.
- 2 Graham JW: Missing data analysis: making it work in the real world. Annual review of psychology 2009;60:549-576.
- 3 Molenberghs G, Fitzmaurice G, Kenward MG, Tsiatis A, Verbeke G (eds): Handbook of Missing Data Methodology Taylor & Francis, 2014.
- 4 Riley SCE, James C, Gregory D, Dingle H, Cadger M: Patterns of recreational drug use at dance events in Edinburgh, Scotland. Addiction (Abingdon, England) 2001;96:1035-1047.
- 5 Miller P, Curtis A, Jenkinson R, Droste N, Bowe SJ, Pennay A: Drug use in Australian nightlife settings: estimation of prevalence and validity of self-report. Addiction (Abingdon, England) 2015;110:1803-1810.
- 6 Calafat A, Blay NT, Hughes K, Bellis M, Juan M, Duch M, Kokkevi A: Nightlife young risk behaviours in Mediterranean versus other European cities: are stereotypes true? European Journal of Public Health 2011;21:311-315.
- 7 Grov C, Kelly BC, Parsons JT: Polydrug use among club-going young adults recruited through time-space sampling. Substance use & misuse 2009;44:848-864.
- 8 Vallance K, Roth E, Thompson K, Chow C, Martin G: Partying last weekend: Factors related to heavy episodic drinking among people who use recreational drugs. Substance use & misuse 2016;51:1731-1740.
- 9 Kelly BC, Wells BE, Leclair A, Tracy D, Parsons JT, Golub SA: Prevalence and correlates of prescription drug misuse among socially active young adults. The International journal on drug policy 2013;24:297-303.
- 10 Duff C: Party drugs and party people: examining the 'normalization' of recreational drug use in Melbourne, Australia. International Journal of Drug Policy 2005;16:161-170.
- 11 Miller BA, Holder HD, Voas RB: Environmental strategies for prevention of drug use and risks in clubs. Journal of substance use 2009;14:19-38.
- 12 Miller BA, Byrnes HF, Branner AC, Voas R, Johnson MB: Assessment of club patrons' alcohol and drug use: the use of biological markers. American journal of preventive medicine 2013;45:637-643.
- 13 Pennay A, Jenkinson R, Quinn B, Droste NT, Peacock A, Lubman DI, Miller PG: Investigating differences between drugs used in the Australian night-time economy: Demographics, substance use, and harm. Substance use & misuse 2017;52:71-81.
- 14 Bourdeau B, Miller BA, Voas RB, Johnson MB, Byrnes HF: Social drinking groups and risk experience in nightclubs: latent class analysis. Health, Risk & Society 2017;19:316-335.
- 15 Fernandez-Calderon F, Cleland CM, Palamar JJ: Polysubstance use profiles among electronic dance music party attendees in New York City and their relation to use of new psychoactive substances. Addictive behaviors 2018;78:85-93.
- 16 Hannemann T-V, Kraus L, Piontek D: Consumption patterns of nightlife attendees in Munich: A Latent-Class Analysis. Substance use & misuse 2017;52:1511-1521.
- 17 Peacock A, Norman T, Bruno R, Pennay A, Droste N, Jenkinson R, Quinn B, Lubman DI, Miller P: Typology of alcohol consumers in five Australian nighttime entertainment districts. Drug and alcohol review 2016;35:539-548.
- 18 Ramo DE, Grov C, Delucchi K, Kelly BC, Parsons JT: Typology of club drug use among young adults recruited using time-space sampling. Drug and alcohol dependence 2010;107:119-127.
- 19 Sanudo A, Andreoni S, Sanchez ZM: Polydrug use among nightclub patrons in a megacity: A latent class analysis. The International journal on drug policy 2015;26:1207-1214.
- 20 Nordfjaern T, Edland-Gryt M, Bretteville-Jensen AL, Buvik K, Gripenberg J: Recreational drug use in the Oslo nightlife setting: study protocol for a cross-sectional time series using biological markers, self-reported and qualitative data. BMJ open 2016;6:e009306.
- 21 Gjerde H, Nordfjaern T, Bretteville-Jensen AL, Edland-Gryt M, Furuhaugen H, Karinen R, Oiestad EL: Comparison of drugs used by nightclub patrons and criminal offenders in Oslo, Norway. Forensic science international 2016;265:1-5.

- 22 Bosker WM, Huestis MA: Oral fluid testing for drugs of abuse. *Clinical chemistry* 2009;55:1910-1931.
- 23 Dyer KR, Wilkinson C: The detection of illicit drugs in oral fluid: another potential strategy to reduce illicit drug-related harm. *Drug and alcohol review* 2008;27:99-107.
- 24 Øiestad EL, Johansen U, Christophersen AS: Drug screening of preserved oral fluid by liquid chromatography-tandem mass spectrometry. *Clinical chemistry* 2007;53:300-309.
- 25 Muthen B, Muthen LK: Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. *Alcoholism, clinical and experimental research* 2000;24:882-891.
- 26 Bergman LR, Magnusson D: A person-oriented approach in research on developmental psychopathology. *Development and psychopathology* 1997;9:291-319.
- 27 Collins LM, Lanza, S. T.: *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences.* John Wiley & Sons, 2010.
- 28 Johnson MB, Voas RA, Miller BA, Holder HD: Predicting drug use at electronic music dance events: self-reports and biological measurement. *Eval Rev* 2009;33:211-225.
- 29 Magura S, Kang SY: Validity of self-reported drug use in high risk populations: a meta-analytical review. *Substance use & misuse* 1996;31:1131-1153.
- 30 Palamar JJ, Salomone A, Gerace E, Di Corcia D, Vincenti M, Cleland CM: Hair testing to assess both known and unknown use of drugs amongst ecstasy users in the electronic dance music scene. *The International journal on drug policy* 2017;48:91-98.
- 31 Gripenberg-Abdon J, Elgan TH, Wallin E, Shaafati M, Beck O, Andreasson S: Measuring substance use in the club setting: a feasibility study using biochemical markers. *Substance abuse treatment, prevention, and policy* 2012;7:7.
- 32 Cone EJ: Oral fluid results compared to self reports of recent cocaine and heroin use by methadone maintenance patients. *Forensic science international* 2012;215:88-91.
- 33 Denis C, Fatséas M, Beltran V, Bonnet C, Picard S, Combourieu I, Daulouède J-P, Auriacombe M: Validity of the self-reported drug use section of the Addiction Severity Index and associated factors used under naturalistic conditions. *Substance use & misuse* 2012;47:356-363.
- 34 Neale J, Robertson M: Comparisons of self-report data and oral fluid testing in detecting drug use amongst new treatment clients. *Drug and alcohol dependence* 2003;71:57-64.
- 35 Yonkers KA, Howell HB, Gotman N, Rounsaville BJ: Self-report of illicit substance use versus urine toxicology results from at-risk pregnant women. *Journal of substance use* 2011;16:372-389.
- 36 Casbon TS, Curtin JJ, Lang AR, Patrick CJ: Deleterious effects of alcohol intoxication: Diminished cognitive control and its behavioral consequences. *Journal of Abnormal Psychology* 2003;112:476-487.
- 37 Peterson JB, Rothfleisch J, Zelazo PD, Pihl RO: Acute alcohol intoxication and cognitive functioning. *Journal of Studies on Alcohol* 1990;51:114-122.

Table 1. Demographic-, behavioral-, and substance-use characteristics of the sample (N = 1,085)

Variables	estimate
Demographics	
	% [95% CI]
Male*	63.7% [60.8, 66.5]
Age:*	
16-24 years	43.6% [40.7, 46.6]
25-34 years	39.4% [36.5, 42.3]
35+ years	12.9% [11.0, 15.0]
Education (≥ college degree)	63.9% [61.0, 66.7]
Current occupational status:	
Employed	65.1% [62.2, 67.9]
Student	28.5% [25.9, 31.2]
Other	6.5% [5.1, 8.1]
Minority background	10.9% [9.3, 12.6]
Self-reported risk behaviors	
	% [95% CI]
Current smoking status:	
Non-smoker	63.7% [60.8, 66.5]
Occasional smoker	23.2% [20.8, 25.8]
Daily smoker	13.1% [11.2, 15.2]
Visiting licensed premises ≥ 2-3 times/week	15.0% [13.0, 17.3]
Alcohol intoxicated ≥ 2-3 times/week	36.0% [33.2, 38.9]
Physical violence involvement	9.3% [7.7, 11.2]
Self-reported substance use	
	% [95% CI] or M [95% CI]
Cannabis (lifetime prevalence)	66.5% [63.6, 69.3]
Cocaine (lifetime prevalence)	25.4% [22.8, 28.1]
MDMA/Ecstasy (lifetime prevalence)	20.6% [18.2, 23.1]
Amphetamine (lifetime prevalence)	15.7% [13.5, 18.0]
Cannabis (past year prevalence)	41.9% [38.9, 44.9]
Cocaine (past year prevalence)	14.3% [12.3, 16.6]
MDMA/Ecstasy (past year prevalence)	10.7% [9.0, 12.8]
Amphetamine (past year prevalence)	5.7% [4.5, 7.4]
Cannabis (# occasions past year)	6.2 [5.3, 7.0]
Cocaine (# occasions past year)	1.3 [0.9, 1.6]
MDMA/Ecstasy (# occasions past year)	0.65 [0.4, 0.8]
Amphetamine (# occasions past year)	0.52 [0.3, 0.7]
Age of first use (any drug)**	18.0 [17.7, 18.3]
Positive oral fluid samples*** or BAC-levels at interview	
	% [95% CI]
Any illicit substance	24.7% [22.2, 27.4]
THC	13.1% [11.2, 15.2]
Cocaine	13.7% [11.8, 15.9]
BAC level ≥ 1.2 g/L	31.9% [29.2, 34.7]

Note: Estimates reflect valid *n*'s for each variable. *15 missing for gender, 45 missing age; ** available for 631 participants; *** Analyzed in laboratory for a total of 30 illicit drugs.

Table 2. Demographic-, behavioral-, and substance-use characteristics of the sample across five identified groups of drug users.

<i>Variables</i>	<i>Never users</i> <i>n = 335 (31%)</i>	<i>Previous users</i> <i>n = 240 (22%)</i>	<i>Cannabis mainly users</i> <i>n = 288 (26%)</i>	<i>Multiple drugs users</i> <i>n = 158 (15%)</i>	<i>Incomplete info</i> <i>n = 64 (6%)</i>
<i>Demographics</i>	% [95% CI]	% [95% CI]	% [95% CI]	% [95% CI]	% [95% CI]
Gender:					
Female	42.4% [31.2, 47.8]	37.1% [31.1, 43.4]	29.9% [24.9, 35.4]	26.6% [20.2, 34.0]	31.3% [21.0, 43.7]
Male	56.7% [51.3, 61.9]	62.9% [56.6, 68.8]	68.8% [63.1, 73.8]	72.1% [64.6, 78.6]	59.4% [46.9, 70.7]
Missing	0.9% [0.3, 3.0]	0.0%	1.3% [0.5, 3.6]	1.3% [0.3, 4.9]	9.3% [4.2, 19.4]
Age:					
16-24 years	41.8% [36.6, 47.2]	35.4% [29.6, 41.7]	54.1% [48.4, 59.9]	46.2% [38.5, 54.0]	29.7% [19.7, 42.0]
25-34 years	37.9% [32.9, 43.2]	42.1% [35.9, 48.4]	38.2% [32.7, 43.9]	40.5% [33.1, 48.4]	39.0% [27.9, 51.5]
35+ years	16.4% [12.8, 20.8]	20.0% [15.4, 25.6]	3.5% [1.8, 6.3]	9.5% [5.8, 15.2]	18.8% [10.1, 30.3]
Missing	3.9% [2.2, 6.6]	2.5% [1.1, 5.4]	4.1% [2.4, 7.2]	3.7% [1.7, 8.2]	12.5% [6.3, 23.2]
Education (≥ college degree)	67.5% [62.3, 72.3]	70.4% [64.3, 75.8]	60.4% [54.6, 65.9]	53.1% [45.3, 60.1]	62.5% [50.0, 73.4]
Current occupational status:					
Employed	66.3% [61.0, 71.1]	74.6% [68.7, 79.7]	59.0% [53.2, 64.6]	63.3% [55.5, 70.4]	54.7% [42.3, 66.5]
Student	27.8% [23.2, 32.8]	21.2% [16.5, 26.9]	35.8% [30.4, 41.5]	28.5% [21.9, 36.0]	26.5% [17.1, 38.8]
Other	5.9% [3.9, 9.1]	4.2% [2.2, 7.6]	5.2% [3.1, 8.5]	8.2% [4.8, 13.7]	18.8% [10.9, 30.3]
Minority background	11.9% [8.9, 15.9]	11.2% [7.8, 15.9]	10.8% [7.7, 14.9]	7.6% [4.5, 12.9]	12.5% [6.3, 23.2]
<i>Self-reported risk behaviors</i>					
Current smoking status:					
Non smoker	80.9% [76.3, 84.8]	73.3% [67.4, 78.6]	52.1% [46.3, 57.8]	34.8% [27.8, 42.6]	60.9% [48.5, 72.1]
Occasional smoker	13.1% [9.9, 17.2]	19.2% [14.6, 24.7]	29.5% [24.5, 35.1]	39.2% [31.9, 47.1]	23.4% [14.6, 35.4]
Daily smoker	5.9% [3.9, 9.1]	7.5% [4.8, 11.6]	18.4% [14.3, 23.3]	25.9% [19.7, 33.4]	15.6% [8.6, 26.7]
Licensed premises ≥ 2-3 times/week	7.8% [5.3, 11.2]	10.0% [6.7, 14.5]	20.8% [16.5, 25.9]	26.6% [20.2, 34.0]	17.2% [9.7, 28.6]
Alcohol intoxicated ≥ 2-3 times/week	24.8% [20.4, 29.7]	35.0% [29.2, 41.2]	44.8% [39.1, 50.6]	49.4% [41.6, 57.1]	25.6% [17.1, 38.8]
Physical violence involvement	3.6% [2.0, 6.2]	4.6% [2.5, 8.1]	14.9% [11.3, 19.51]	20.8% [15.2, 27.9]	3.1% [0.8, 11.8]
<i>Self-reported substance use</i>					
	<i>M [95% CI]</i>	<i>M [95% CI]</i>	<i>M [95% CI]</i>	<i>M [95% CI]</i>	<i>M [95% CI]</i>
Cannabis (# occasions past year)	--	0	11.5 [9.6, 13.3]	18.3 [15.1, 21.5]	12.4 [2.6, 22.2]
Cocaine (# occasions past year)	--	0	0 [0.0, 0.0]	7.8 [5.8, 9.7]	3.2 [0.2, 6.3]
MDMA/Ecstasy (# occasions past year)	--	0	0.3 [0.2, 0.5]	3.2 [2.1, 4.2]	2.5 [-0.5, 5.4]

Amphetamine (# occasions past year)	--	0	0 [0.0, 0.0]	2.8 [1.5, 4.0]	3.5 [-1.0, 8.1]
Age of first use (any drug)	--	19.3 [18.8, 19.8]	17.9 [17.6, 18.3]	16.6 [16.1, 17.2]	16.9 [15.9, 17.9]
<i>Positive oral fluid samples/BAC-levels</i>	% [95% CI]				
Any illicit substance	13.1% [9.9, 17.2]	7.9% [5.1, 12.1]	29.1% [24.2, 34.7]	62.7% [54.8, 69.9]	34.4% [23.7, 46.9]
THC	3.9% [2.2, 4.3]	1.7% [0.6, 4.4]	21.8% [17.5, 27.0]	31.0% [24.3, 38.7]	20.3% [12.1, 32.0]
Cocaine	8.4% [5.8, 11.8]	5.4% [3.2, 9.1]	10.0% [7.1, 14.1]	44.7% [36.1, 51.5]	15.9% [8.7, 27.2]
BAC level \geq 1.2 g/L	24.5% [20.2, 29.4]	31.7% [26.1, 37.8]	29.2% [24.2, 34.7]	43.7% [36.1, 51.5]	54.7% [42.3, 66.5]

Table 3. Association between drug user groups and drug-test indicators of recent substance use (illicit substances and alcohol); unadjusted and adjusted logistic regression models

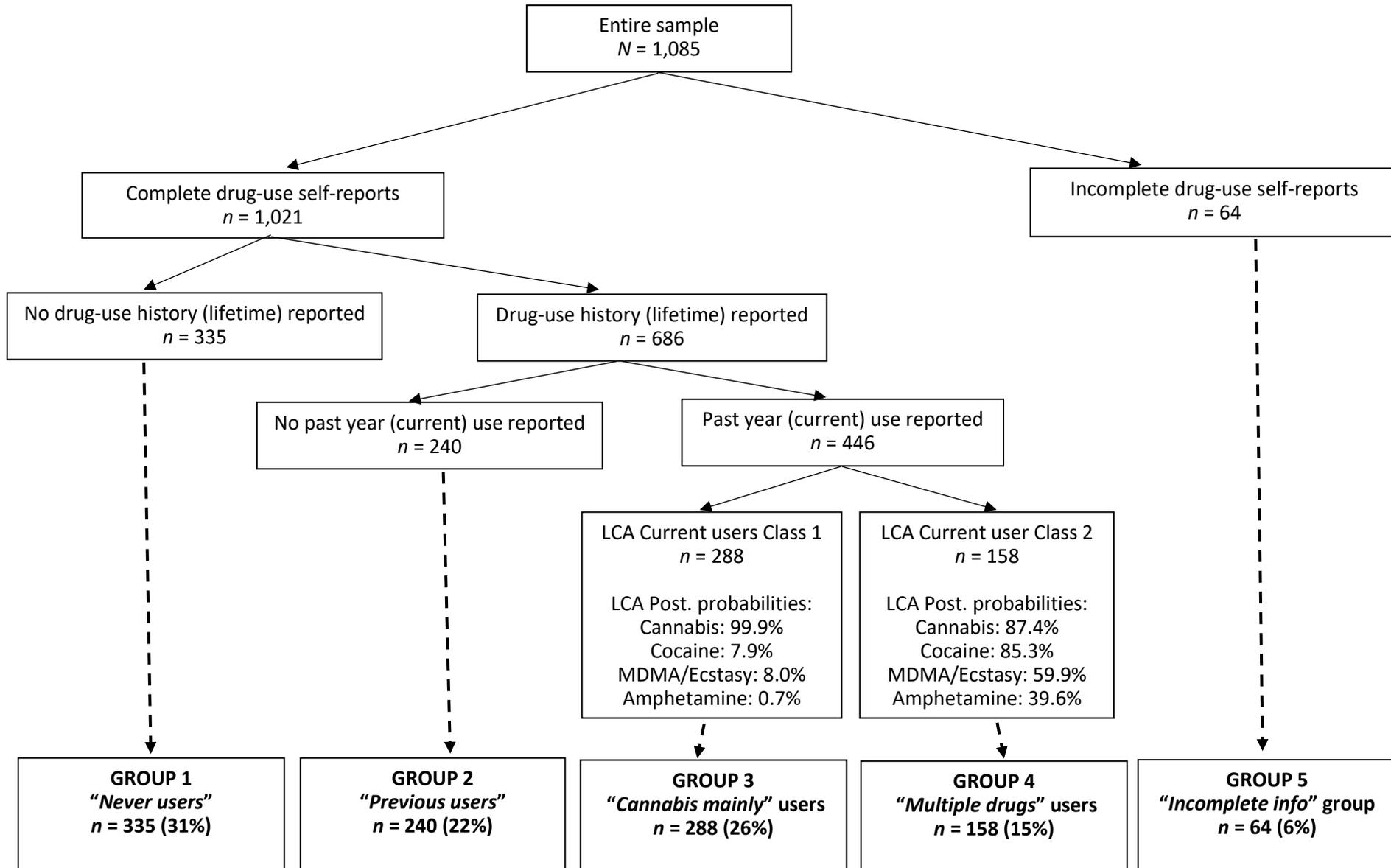
	Model 1: Oral fluid sample positive Any illicit substance	Model 2: Oral fluid sample positive THC	Model 3: Oral fluid sample positive Cocaine	Model 4: BAC level ≥ 1.2 g/L
Unadjusted models^a	OR [95% CI]	OR [95% CI]	OR [95% CI]	OR [95% CI]
<i>Illicit drug use groups</i>				
Never users (ref.)	1.00	1.00	1.00	1.00
Previous users	0.57 [0.3, 1.0] *	0.42 [0.1, 1.3]	0.63 [0.3, 1.2]	1.43 [0.99, 2.1]
Cannabis mainly users	2.72 [1.8, 4.1] ***	6.93 [3.7, 12.9] ***	1.23 [0.7, 2.1]	1.27 [0.89, 1.8]
Multiple drugs users	11.09 [7.1, 17.4] ***	11.13 [5.8, 21.3] ***	8.5 [5.1, 13.9] ***	2.39 [1.6, 3.6] ***
Incomplete	3.46 [1.9, 6.3] ***	6.3 [2.8, 14.4] ***	2.0 [0.95, 4.5]	3.72 [2.1, 6.5] ***
Adjusted models^b	aOR [95% CI]	aOR [95% CI]	aOR [95% CI]	aOR [95% CI]
<i>Illicit drug use groups</i>				
Never users (ref.)	1.00	1.00	1.00	1.00
Previous users	0.52 [0.1, 0.93] *	0.37 [0.12, 1.20]	0.57 [0.29, 1.2]	1.41 [0.96, 2.1]
Cannabis mainly users	1.71 [1.1, 2.7] *	3.55 [1.8, 6.9] ***	0.94 [0.52, 1.7]	1.16 [0.79, 1.7]
Multiple drugs users	6.46 [3.9, 10.7] ***	5.21 [2.5, 10.7] ***	6.14 [3.5, 10.8] ***	2.07 [1.3, 3.2] *
Incomplete	2.62 [1.4, 5.0] ***	4.41 [1.8, 10.8] ***	1.75 [0.78, 3.9]	3.37 [1.9, 6.0] ***

Note:

Shown are the estimates from unadjusted odd ratios (OR); 95% CI^a and adjusted (adjusted odd ratios (aOR); 95% CI)^b logistic regression models examining the putative associations between the identified user groups and four drug-tests indicative of recent substance use. All adjusted models accounted for gender, age, education, occupational status, minority background, music preferences, smoking, and risk behaviors (coefficients not shown). The substantive predictor of interest -- drug user groups -- was modelled as a categorical variable in all models, with “Never users” as a reference; * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Follow-up contrasts of the three user groups revealed that “Multiple drugs” users were significantly more likely to have positive oral fluid tests for any illicit substance and for cocaine than either “Cannabis mainly” [aOR = 3.77 (2.42 – 5.84) for any illicit substance; aOR = 6.56 (3.89 – 11.05) for cocaine] or “Incomplete info” groups [aOR = 2.46 (1.26 – 4.79) for any illicit substance; aOR = 3.50 (1.58 – 7.73) for cocaine]. In terms of oral fluid tests for THC/cannabis, there were no significant differences in odds across three user groups. Finally, in terms of elevated BAC levels, “Multiple drugs” and “Incomplete info” groups were both more likely to test positive than the “Cannabis mainly” users [aOR_{All_drugs} = 1.79 (1.17 – 2.71); aOR_{Incomplete_info} = 2.90 (1.61 – 5.20)].

Figure 1. Identification and classification of drug user groups.



Appendix,

Table A1: Substances analyzed in oral fluid samples and cut-off concentrations

<i>Substance</i>	Cut-off concentrations (µg/L) ^a	<i>Substance</i>	Cut-off concentrations (µg/L) ^a
<i>Amphetamines and analogues:^b</i>		<i>Benzodiazepines and z-hypnotics:</i>	
1. Amphetamine	1.8	17. Diclazepam ^{b,c}	0.024
2. Methamphetamine	1.1	18. Etizolam ^{b,c}	0.026
3. MDMA	0.29	19. Flubromazepam ^{b,c}	0.025
4. Methiopropamine ^c	0.012	20. Phenazepam ^b	0.026
5. 4-methylamphetamine ^c	0.067	<i>Phenethylamines:^b</i>	
<i>Cannabinoids:^b</i>		21. 2C-B ^c	0.029
6. AM-2201 ^c	0.011	22. 2C-I ^c	0.035
7. THC	0.047	23. 25C-NBOMe ^c	0.006
8. UR-144 ^c	0.0094	24. 25I-NBOMe ^c	0.008
9. 5F-APINACA ^c	0.012	25. Ethylphenidate ^c	0.22
10. 5F-PB-22 ^c	0.011	<i>Opioids:</i>	
11. THJ-2201 ^c	0.011	25. 6-acetylmorphine (6-AM) ^b	0.59
<i>Cathinones:^b</i>		<i>Other substances:^b</i>	
12. Methylenedioxypropylvalerone (MDPV) ^c	0.062	27. Dimethyltryptamine ^c	0.014
13. α-Pyrrolidinopentiophenone (alpha-PVP) ^c	0.042	28. Ketamine ^{b,c}	0.043
14. 4-Methylmethcathinone (mephedrone) ^c	0.013	29. LSD	0.002
<i>Tropane alkaloids:^b</i>		30. Salvinorin A ^c	0.39
15. Benzoylcegonine	0.52		
16. Cocaine	0.14		

Note: ^aIn oral fluid-buffer-methanol mixture (expected average: 0.4 mL oral fluid + 0.8 mL buffer+2.0 mL methanol). ^bClassified as illicit in this report. ^cClassified as new psychoactive substances (NPS) in this report.

Appendix A2: Latent Class Analysis (LCA)

Prediction of group membership

In addition to the three *known* groups identified from the self-reported drug use histories (i.e., “Never users”, “Previous users”, and “Incomplete information” groups), we identified a total of 446 participants who a) reported past year use of at least one of the substances where the prevalence estimates exceeded 5%: cannabis (41.9%), cocaine (14.3%), MDMA/ecstasy (10.7%), or amphetamine (5.7%), and b) had complete responses on these variables (i.e., were not previously classified into the “Incomplete information” group). As high levels of heterogeneity have been previously observed within similar samples, we used the Latent Class Analysis (LCA, Collins 2010) to detect and identify the so-far *unknown* groups of drug users in our sample.

LCA was conducted in Stata 15.0 with the general *-gsem* command. A sequence of models (1-3) was fitted to identify an optimal baseline model (Collins 2010). Several starting values were used to avoid the issue of local maxima and to ensure all values converged to identical solutions (Collins 2010). The Bayesian Information Criterion (BIC), and Akaike's information criterion (AIC) were used as the principal indices of best fit (Collins 2010). Based on these indices, the two-class model was selected as the best fit (Table A2.1); even though the three-class solution was also estimated, it did not converge. Table A2.2. shows the latent class marginal probabilities (i.e., the expected proportions of the sample in each identified class, top of Table) and estimated means (i.e., posterior probabilities for our binary drug-use variables, bottom of Table). Each participant was assigned to one class based on the maximum posterior probabilities of class membership.

Table A2.1 Comparison of tested LCA solutions

Model	Obs.	ll (null)	ll (model)	df	AIC	BIC
1-class solution	446	.	-780.809	4	1569.618	1586.019
2-class solution	446	.	-684.4047	9	1386.809	1423.712

Table A2.2. Class characteristics for the selected two-class solution

	Class 1 "Cannabis mainly"	Class 2 "Multiple drugs"
<i>Pr (Class)</i>	0.68	0.32
Cannabis	0.999	0.874
Cocaine	0.078	0.853
MDMA/Ecstasy	0.080	0.599
Amphetamine	0.007	0.396

Collins L. M., Lanza S. T. *Latent Class and Latent Transition Analysis*. Hoboken, New Jersey: John Wiley & Sons, Inc; 2010.