
**Drug Use in Young Adults
Engaging with the Nightlife
Scene: A Longitudinal European
Survey**

by

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Submitted for the degree of Doctor of Philosophy

UCL

June 2020

I, Jon Waldron, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

The use of alcohol and illicit drugs has long been a feature in the nightlife scene. However, there is a current paucity of research on contemporary patterns of drug use in European nightlife populations. Furthermore, there have been considerable developments in the European drug market, potentially placing people at elevated risk of harm. In **Chapter 1**, I provide an overview of this key gap in the literature and introduce the ALAMA-Nightlife project, a multi-country collaboration designed to address this. In **Chapter 2**, I demonstrate that the internet can be successfully used to recruit a sample of young European adults engaging with the nightlife scene, by showing an online sample to be broadly representative in terms of drug use, nightlife engagement and demographics as an offline sample recruited at nightclubs and festivals. The cross-sectional profiles of drug use are examined in **Chapter 3**, with Latent Class Analysis revealing six distinct subgroups indicating substantial heterogeneity in drug use patterns. Furthermore, increasing levels of polydrug use were associated with higher scores on indices of problematic alcohol and drug use. In **Chapter 4**, I examined the relationship between harm reduction and polydrug use, and identified five discrete patterns of personal protective strategies that differed in levels of polydrug use. Extensive endorsement of harm reduction behaviours was also associated with more positive and fewer negative consequences following drug use. Longitudinal trajectories of drug use in the European nightlife scene are assessed in **Chapter 5**, with findings suggesting considerable stability over the course of 12 months. Amongst the small percentage whose use did change at follow-up, both an increase and decrease were associated with lower perceptions of risk, while increasing or decreasing the number of electronic dance music events attended was associated with a corresponding change in drug use. In **Chapter 6**, I summarise these findings, discuss their implications and how they address current gaps in the evidence while considering their limitations, and suggest areas for future research on drug use in the European nightlife scene.

Impact Statement

Each study presented in this thesis makes a novel contribution to the literature concerning drug use in the European nightlife scene. Findings help address the lack of research into contemporary patterns of drug use in this population given recent drug market developments, and are highly relevant for both future research and the design of interventions to reduce drug related harm.

The finding that a nightlife sample recruited online was broadly representative of an offline sample recruited at nightclubs and festivals suggests the internet can serve as a useful tool for regularly monitoring trends in drug use in this population. However, that small differences were found shows the necessity of continuing efforts to validate online samples. The novel and successful application of mixture modelling techniques (Latent Class Analysis and Latent Transition Analysis) to identify cross-sectional profiles and longitudinal trajectories of drug use show the utility of these methods for future assessments of patterns of drug use in the European nightlife scene.

Research presented here is also potentially informative for those designing and delivering interventions to mitigate drug related harm in the nightlife scene. The identification of six heterogeneous cross-sectional profiles of drug use suggests that intervention efforts should target such subgroups accordingly, for example by highlighting the risks of different drug combinations. A further novel study in this thesis demonstrated considerable longitudinal stability in drug use, suggesting little change in patterns of drug use over 12 months and that interventions should consider efforts to prevent or reduce potentially risky use in the longer term. This thesis also presents the first study to model harm reduction profiles, and found more widespread strategy adoption to be associated with fewer negative, and to a greater extent more positive experiences following drug use. Thus, the design of interventions and future research should now consider the positive experiences sought from drug use as part of the approach to harm reduction, as it is likely that messages that both mitigate risk and promote a more enjoyable experience will be the most salient for nightlife populations.

Research presented in this theses has been published, or is in the process of being prepared for publication, in peer-reviewed journals and reports (details below), and has been

presented at three conferences: British Association of Psychopharmacology, Club Health and Lisbon Addictions. Outside of academia, work has been presented at the public engagement event Pint of Science, and the study has been discussed in online articles written for The Guardian and BBC.

The work presented in this thesis has given rise to the following publications:

Waldron, J. & Grabski, M. (In press). ALAMA-Nightlife Survey: Exploring drug use trajectories in the European nightlife scene, *Insights: Online Surveys*, European Monitoring Centre for Drugs and Drug Addiction, Lisbon.

Waldron, J., Grabski, M., Freeman, T.P., Mokrysz, C., Hindocha, C., Measham, F., van Beek, R., van der Pol, P., Hauspie, B., Dirx, N., Schrooten, J., Elgán, T.H., Feltmann, K., Benedetti, E., Scalia Tomba, G., Fabi, F., Molinaro, S., Gripenberg, J., van Havere, T., van Laar, M. & Curran, H.V., (2020) How do online and offline sampling compare in a multinational study of drug use and nightlife behavior in Europe? *International Journal of Drug Policy*, 82, 102812

Waldron, J. & Curran, H.V. (2018), The drugs being used at UK festivals. *BBC News*, Available online: <https://www.bbc.co.uk/news/uk-44482290>

Waldron, J., Grabski, M., Mokrysz, C., Freeman, T.P. & Measham, F., (2017), Just say 'know' to drugs: can testing facilities make festivals safer? *The Guardian*, Available online: <https://www.theguardian.com/science/sifting-the-evidence/2017/aug/10/just-say-know-to-drugs-can-testing-facilities-make-festivals-safer>

Acknowledgements

I have found doing my PhD to be a thoroughly enjoyable and rewarding experience. I owe this pleasure to the brilliant people I have met and worked with over the past four years, and to those who have supported me every step of the way, to all of whom I will be eternally grateful.

Firstly, I would like to thank to my supervisor, Val Curran. Val is incredibly kind and caring, and ensures that everyone under her guidance feels fully supported whilst also being intellectually stimulated. It has been an utter privilege to be part of the CPU, in which Val has created an atmosphere that strives for excellence whilst also being warm and caring. I must also thank Tom Freeman for acting as my secondary supervisor. While setting a fantastic example with the exceptional quality of his work, Tom is an incredibly fun guy which has made my time working with him a real pleasure. He also never seems to get irritated by the quick questions, no matter how trivial, and his support has been absolutely invaluable. I have learned a great deal from Val and Tom, so thank you both for being such attentive and caring supervisors.

I would like to give a special thanks to Meryem Grabski, as without her I don't think this thesis would have been possible. Meryem has been fantastic to work with over the past three years, and at times has definitely taken on more than her fair share to let me focus on escaping the statistical abyss! I feel very fortunate to have worked so closely with someone I see eye to eye with, and the fact there have been no major 'tuk tuk on tracks' situations with work has made my project-thesis juggle so much easier. Thanks for everything, and I'm really looking forward to working on the ALAMA extension with you Meryem!

I have felt very lucky to have been part of such a mutually supportive and friendly research team, so a huge thanks to everyone else at the CPU (past and present): Claire Mokrysz, Will Lawn, Em Thomas, Katie Walsh, Ravi Das, Chandni Hindocha, Grace Gale, Kat Petrilli, Rachel Lees, Beth Marsh, Anya Borissova, Luzia Troebinger, Guilia Piazza, Vanessa Hennessy, Sunjeev Kamboj, Sharinjeet Dhiman, Leah Markwick, Emma Cawley and Louise Simeonov.

I have shared a PhD office with some amazing people, but a particular thanks has to go to Jem Bhatt, Em Thomas, Katie Walsh and Charlotte Stoner. There is no doubt whatsoever that without your friendship I would not have been able to deal with everything in the past

three years. Your perspective on life has been invaluable, so thank you so much for your kindness and for tirelessly listening to my moaning! I miss Wednesday's!

Thank you also to everyone who participated in my research, and to the ALAMA-Nightlife consortium: Ruben van Beek, Margriet van Laar, Peggy van der Pol, Tina van Havere, Bert Hauspie, Jochen Schrooten, Nicky Dirx, Kristen Feltmann, Johanna Gripenberg, Tobias Elgán, Nicklas Kartengren, Elisa Benedetti and Sabrina Molinaro. Your expertise has been extremely helpful, and it has been a privilege to work in collaboration with such a talented group of researchers.

Thanks also to my mates for putting up with me, and for somehow still seemingly being happy to entertain me rambling on about my research. Cheers Daves! I would also like to thank my Mum, Gill, my Dad, Tony, and my Brother, Rich, for their continued love and support.

Above all, my greatest thanks goes to my Dad. He gently nudged me back into academia to do my first masters, which opened my eyes to the world of research and led to this PhD, and one day I hope to reach the heights he has. He is my inspiration and hero, and this thesis is dedicated to him.

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List of Abbreviations

4FA	4-Fluoroamphetamine
5-HTP	5-Hydroxytryptophan
95% CI	95% Confidence Interval
aBIC	Adjusted Bayesian Information Criterion
AIC	Akaike Information Criterion
ALAMA-Nightlife	A Longitudinal and Momentary Analysis in Nightlife
ANOVA	Analysis of Variance
AUDIT-C	Alcohol Use Disorders Identification Test for Consumption
BCH	Bolck, Croon, and Hagenaaars
BIC	Bayesian Information Criterion
DIMS	Drug Information Monitoring System
DUDIT	Drug Use Disorders Identification Test
EFA	Exploratory Factor Analysis
EMA	Ecological Momentary Assessment
EMCDDA	European Monitoring Centre for Drugs and Drug Addiction
EMSS	Electronic Music Scene Survey
ESPAD	European School Survey Project on Alcohol and Other Drugs
GAD-2	Generalised Anxiety Disorder 2-item
GDS	Global Drug Survey
GHB	γ -Hydroxybutyric Acid
HR	Harm Reduction
LCA	Latent Class Analysis
LMR-LRT	Lo-Mendell-Rubin Likelihood Ratio Test
LSD	Lysergic Acid Diethylamide
LTA	Latent Profile Analysis
MDA	3,4-Methylenedioxyamphetamine
MDMA	3,4-Methylenedioxymethamphetamine
NPS	New Psychoactive Substances
ONS	Office for National Statistics
OR	Odds Ratio
PD	Polydrug
PHQ-2	Patient Health Questionnaire-2
WHO	World Health Organisation
WHO-5	World Health Organisation-5

Chapter 1: General Introduction

Work presented in this chapter gave rise to the following publication:

Waldron, J. & Grabski, M. (In press). ALAMA-Nightlife Survey: Exploring drug use trajectories in the European nightlife scene, Insights: Online Surveys, European Monitoring Centre for Drugs and Drug Addiction, Lisbon.

1.1 Background

The last twenty years have witnessed an upsurge in the European nightlife scene. The evolution and commercialisation of the electronic dance music scene has been a major contributor to this growth, expanding from underground ‘raves’ in the late 1980s and early 1990s to large, organised parties held in licensed premises such as nightclubs and festivals (Anderson & Kavanaugh, 2007; Hubbard, 2017).

The link between engagement with the nightlife scene and the use of alcohol and illicit substances has long been established (Calafat, Fernandez, Juan, & Becona, 2008; McCambridge, Mitcheson, Winstock, & Hunt, 2005; Measham, Aldridge, & Parker, 2001; Nordfjærn, Bretteville-Jensen, Edland-Gryt, & Gripenberg, 2016; Palamar, Acosta, & Cleland, 2019; Winstock, Griffiths, & Stewart, 2001). Studies investigating young adults’ motivations to use licit and illicit drugs highlight that most do so to enhance their enjoyment when engaging with the nightlife scene. For example, ecstasy is often consumed to heighten social interaction given the acute prosocial effects of MDMA (Kamilar-Britt & Bedi, 2015; Peters & Kok, 2009). Other commonly cited reasons for drug use in the nightlife scene include relaxation, increased energy, euphoria, staying awake, sensation seeking and sexual pleasure (Boys, Marsden, & Strang, 2001; Halkitis, Mukherjee, & Palamar, 2007; Parks & Kennedy, 2004; Ramo, Grov, Delucchi, Kelly, & Parsons, 2010; Ter Bogt & Engels, 2005).

The use of drugs for their perceived positive effects, however, should be weighed against the potential for negative consequences and adverse impacts on health. In addition to acute intoxication, the risks associated with drug use in the nightlife scene may include

violence, accidents, driving or being driven by someone under the influence, risky or unwanted sex, poor sleep, emergency medical treatment and, in extreme cases, death (Calafat et al., 2010; Calafat et al., 2011; Chinet, Stéphan, Zobel, & Halfon, 2007; Gripenberg-Abdon et al., 2012; Montgomery, Fisk, Wareing, & Murphy, 2007; Nordfjærn et al., 2016; Taurah, Chandler, & Sanders, 2014). A number of psychological problems have also been observed in the days after drug use, including impaired cognitive functioning, anxiety and depressed mood (Chinet et al., 2007; Curran & Travill, 1997; Montgomery et al., 2007; Parrott & Lasky, 1998; Taurah et al., 2014).

Furthermore, a number of drug users in the nightlife scene are thought to be polydrug users, potentially compounding the risks of negative health outcomes (Winstock et al., 2001). Polydrug use is defined as the use of two or more substances at the same time or use of one while under the influence of another (Barrett, Darredeau, & Pihl, 2006; Grov, Kelly, & Parsons, 2009), or the use of multiple substances over a given period of time, such as 12 months (Connor, Gullo, White, & Kelly, 2014; Martin, 2008). Given that use of drugs in combination is not the same behaviour as the use of different substances separately over a given time period, the group that the term 'polydrug users' refers to cannot be said to be homogenous. As such, despite some evidence suggesting that there is cross-over between these groups in that a number of people engage in both behaviours (Quek et al., 2013), the distinction should be made between them, potentially by the use of narrower terminologies such as 'separate polydrug users' and 'simultaneous polydrug users', and where wider terms are used it must be made clear which behaviour is being referred to. For reasons of brevity, the terms 'polydrug use' and 'polydrug users' have been adopted in this thesis, and where used refers to the use of multiple drugs over the course of 12 months, and not to the use of different drugs in combination with each other.

Polydrug users are potentially at greater risk of drug related harm given the different temporal patterns of use, different timings of drugs' peak effects and resulting drug interactions (F. Fernández-Calderón et al., 2014; Quek et al., 2013; Smith, Farrell, Bunting, Houston, & Shevlin, 2011). Indeed, higher levels of polydrug use under both definitions have been associated with more self-reported mental health problems, increased depression and reduced cognitive functioning, as well as an increased risk of overdose and death (Agrawal, Lynskey, Madden, Bucholz, & Heath, 2007; Baggio, Studer, Mohler-Kuo, et al., 2014; Connor et al., 2014; F. Fernández-Calderón et al., 2014; Grov et al., 2009; Hunt, Evans, Moloney, & Bailey, 2009; Scott, Roxburgh, Bruno, Matthews, & Burns, 2012).

Indeed, differing drug combinations have been associated with particular risks to health. For example, the concurrent use of alcohol and cocaine results in a metabolic reaction in the liver that results in the synthesis of a new metabolite, cocaethylene, that is associated with increased effects of intoxication and tachycardia (McCance-Katz et al., 1993). Similarly, the co-use of multiple stimulants is associated with an increase in cardiovascular risk (Ghuran & Nolan, 2000; Macmahon & Tallentire, 2010), while the combination of central nervous system depressants, such as prescription opioids and benzodiazepines, increases the risk of blackouts, overdose and death (Gudin, Mogali, Jones, & Comer, 2013; Jones, Mogali, & Comer, 2012).

Studies using methods such as Latent Class Analysis (LCA) to define subgroups of polydrug user in the general population converge on findings that differentiate groups simply in terms of the overall number of drugs used (e.g. Smith et al., 2011). However, patterns in populations with higher levels of drug use reveal that polydrug use may not be a purely additive phenomenon (e.g. Morley, Lynskey, Moran, Borschmann, & Winstock, 2015). Given the association between polydrug use and nightlife engagement, particularly with the electronic dance music scene (Connor et al., 2014; Grov et al., 2009; Winstock et al., 2001), it seems this would be an ideal population in which to employ methods such as LCA to further our understanding of polydrug use. However, there is a paucity of such research in the European nightlife scene, a key gap in the literature which is discussed in detail in Chapter 3.

1.2 Trajectories of drug use in the nightlife scene

The vast majority of studies into drug use in the European nightlife scene have been cross-sectional (e.g. Calafat et al., 2010; Calafat et al., 2011; Measham, Wood, Dargan, & Moore, 2011; Van Havere, Tutenges, De Maeyer, Broekaert, & Vanderplasschen, 2015; Vervaeke, Van Deursen, & Korf, 2008). While such studies are extremely useful for understanding contemporary patterns of drug use and identifying potentially high risk groups, they are unable to elucidate changes over time and factors potentially associated with escalation, decline or maintenance of drug use.

Prospective, longitudinal designs are more informative about the changing dynamics of drug use in nightlife scenes, but existing studies have been conducted in settings outside of Europe and indeed may now be outdated. One such study followed 450 gay and bisexual clubbers in New York City over the course of 12 months to investigate drug use trajectories.

With respect to polydrug use, the frequency of amphetamine, ecstasy and GHB use was found to be highly related over the course of the study, leaving the authors to conclude that polysubstance use is a real and consistent behaviour amongst this population (Halkitis, Palamar, & Mukherjee, 2007). Trajectories of methamphetamine use were also assessed, with higher levels of sensation seeking and using to avoid unpleasant emotions associated with consistent and more frequent use (Halkitis, Mukherjee, et al., 2007).

A separate study, also conducted in New York, aimed to examine 12 month cocaine use trajectories amongst 400 young adult clubbers (Ramo, Grov, Delucchi, Kelly, & Parsons, 2011). Those with the most frequent use at follow-up were found to have the highest levels of baseline drug dependence and were more likely to have recently used alcohol. The majority of the sample was also found to maintain their cocaine use over the course of the study, while changes in use were not related to baseline use of other 'club drugs' (ecstasy, methamphetamine, ketamine, GHB or LSD), leading the authors to conclude that cocaine is the primary drug of choice in nightlife amongst this population.

Longitudinal patterns of ecstasy use have also been assessed in Australian clubbers. Smirnov et al (2013) followed 297 young adult ecstasy users over 30 months and identified low, medium and high use trajectories. Membership of the high and intermediate use groups was predicted by higher lifetime use (70 pills or more), but not drug dependence, at baseline and frequent attendance at electronic dance music events, while heavier use was also associated with recent cannabis use at follow-up. Interestingly, members of the high and medium use trajectories reduced the frequency of their use over 30 months, and high use members were unlikely to have used for more than three years at baseline. This suggests that there may be a natural cessation to ecstasy use, with the authors concluding that ecstasy trajectories may better be understood in terms of environmental or circumstantial rather than addictive use patterns.

A further study of Australian ecstasy users examined the relationship between attendance at various nightlife venues and frequency of ecstasy use over 30 months (Leslie et al., 2015). Above all other venues, monthly or greater attendance at nightclubs increased the risk of frequent (at least monthly) use of ecstasy, independent of availability, lifetime use and use by peers. This finding, the authors conclude, highlights that attendance at certain venues may increase the risk of ecstasy related harm, and thus should be targeted for behavioural and educational interventions accordingly.

While substance use is common among nightlife populations, a number of people do not use either licit or illicit drugs (Comis & Noto, 2012; Miller et al., 2015). Understanding the reasons why some never start using or cease their use may be helpful when assessing factors that may protect against the exacerbation of drug use and the risk of negative consequences (Peters, Kok, & Schaalma, 2008). For example, negative impacts on mental health and changing life circumstances, such as a new relationship or job or withdrawal from the dance music scene, have been found to play an important role in peoples' cessation of ecstasy use (Comis & Noto, 2012; Peters & Kok, 2009; Peters et al., 2008; Verheyden, Maidment, & Curran, 2003). Given the role of changing life circumstances, it may be that young clubbers are able to control their drug use in response to social, professional and educational demands. However, drug use can become problematic for some, thus understanding the reasons for cessation, self-regulation and persistence of use in European nightlife populations is crucial for informing the design of interventions.

1.3 Developments in the European drug market

Patterns of use of drugs common in the nightlife scene differ widely between European countries. For example, amphetamines are more commonly used in Scandinavian countries, cocaine is more popular in southern and western Europe, while the use of ecstasy is more dispersed but with comparatively high rates in the Netherlands and UK (EMCDDA, 2019). There have, however, been recent market developments that are likely to affect young adults engaging with the nightlife scene across Europe.

The potency of several drugs commonly used in the nightlife scene has increased markedly in recent years, fuelling health concerns for users who may now be consuming far stronger drugs. Of particular concern is the rise in average MDMA content in a single ecstasy tablet, from between 50 and 80mg in the early 2000s to approximately 125mg today, with 'super strength' tablets containing between 270 and 340mg reported by a number of national drug monitoring systems (Giné et al., 2016; Mounteney et al., 2018). The European Monitoring Centre for Drugs and Drug Addiction (EMCDDA) also report that the number of cocaine seizures and volumes seized in Europe are at an all-time high, and that data from these seizures suggest the purity of cocaine at retail level is the highest it has been in over a decade (EMCDDA, 2019). The availability of high strength ecstasy has been linked to an increase in health related emergencies (GDS, 2016), while deaths attributed to MDMA toxicity have risen over eleven-fold in the UK, from 8 in 2010 to 92 in 2018 (ONS, 2019). Similarly, the rise in purity of cocaine seems to have been accompanied by a rise in deaths

in the UK, with 637 registered deaths associated with cocaine use in 2018, compared to 144 in 2010 (ONS, 2019).

Another key development is the proliferation of new psychoactive substances (NPS) in the European drug market (EMCDDA, 2015), which appear to be increasingly used in the nightlife scene (Hannemann, Kraus, & Piontek, 2017; Korf et al., 2019; Measham et al., 2011; Vento et al., 2014). Indeed, by the end of 2018, the EMCDDA was actively monitoring over 730 of these substances (EMCDDA, 2019). New psychoactive substances are synthetic compounds that are often pharmaceutical analogues of 'traditional' drugs designed to mimic the effects of those parent compounds (Baumeister, Tojo, & Tracy, 2015; Pirona et al., 2017). They are thought to be potentially more dangerous than the drugs they are designed to mimic, and far less is known about them (Baumeister et al., 2015; Giné, Espinosa, & Vilamala, 2014; Hondebrink, Nugteren-van Lonkhuyzen, Van Der Gouwe, & Brunt, 2015; Pirona et al., 2017; Vreeker, van der Burg, van Laar, & Brunt, 2017). Although data on their use are limited, studies suggest that people use NPS both in response to market factors such as the unavailability or poor quality of 'traditional' drugs and the price and availability of NPS, as well as social and environmental factors including setting and positive ratings from peers or online (Freeman et al., 2012; Hondebrink et al., 2015; Linsen et al., 2015; Moore, Dargan, Wood, & Measham, 2013; Vreeker et al., 2017).

1.4 The ALAMA-Nightlife Project

Given the lack of longitudinal studies and recent drug market developments, there is now an urgent need to investigate the relationship between drug use and engagement with the nightlife scene in Europe. Longitudinal studies in different settings (New York, Australia) find differing associations with patterns of drug use, further highlighting the necessity for similar investigations in European populations. Furthermore, such studies are country specific and conducted in relatively small samples. In order to address this gap in the evidence base, the ALAMA-Nightlife (A Longitudinal And Momentary Assessment in Nightlife) Project was established. The project was a collaboration between research institutions and universities from Belgium, Italy, the Netherlands, Sweden and the UK,

funded by the European Research Area Network on Illicit Drugs (ERANID)^{1, 2}. The specific institutions involved were:

- Belgium: HoGent and VAD
- Italy: Consiglio Nazionale delle Ricerche
- Netherlands: Trimbos Instituut
- Sweden: Stockholm förebygger alkohol- och drogproblem (STAD), Karolinska Institutet
- UK: Clinical Psychopharmacology Unit, University College London

The overall objective of the project was to gain insight into drug use and nightlife participation amongst young adults in Europe, and to understand how patterns change over time.

1.5 Electronic Music Scene Survey (EMSS)

To achieve the overall objective of the ALAMA-Nightlife Project, the consortium designed and implemented the EMSS³, a longitudinal online survey into drug use and nightlife behaviour. The UK team at UCL were the work package leaders for the EMSS, and my colleague (Dr Meryem Grabski) and I were jointly responsible for the coordination of all components and steps described below across all five countries. The EMSS is the only work package in which all five countries participated. It was the largest, principal study in the ALAMA-Nightlife project and serves as a ‘backbone’ for all other work packages, providing a source of country-specific information and recruitment into additional studies.

¹ <https://www.eranid.eu/projects/alama-nightlife/>

² In the UK, ALAMA-nightlife is a collaborative project supported by the European Research Area Network on Illicit Drugs (ERANID). This paper is based on independent research commissioned and funded in England by the National Institute for Health Research (NIHR) Policy Research Programme (project ref. PR-ST-0416-10003). The views expressed in this thesis are those of the author and not necessarily those of the national funding agencies or ERANID.

³ <https://www.emssurvey.eu/>

The remainder of this chapter will discuss the design, development and recruitment strategy of the EMSS, from which data for the studies presented herein were used, before concluding with the objective and specific questions this thesis aims to address.

1.5.1 Design

The baseline online survey was conducted between May and November 2017, and participants were contacted by email in 2018 to complete the 12 month follow-up survey. Both baseline and follow-up surveys each took approximately 30 minutes to complete, and, as displayed in Table 1.1, captured data on nightlife engagement, drug use, risks and experiences, harm reduction behaviours and demographic characteristics.

Table 1.1: Areas covered in EMSS baseline and follow-up surveys

Domain	Areas covered
Demographics	<i>Recruitment source; age; gender; country of residence; area code; sexuality; relationship status; urbanicity; education; mothers education.</i>
Nightlife engagement	<i>N events in last 12 months; genre preference; motivations for going out; lifetime and past 12 month venue attendance and frequency (nightclubs, festivals, illegal raves, pubs, house parties); age of first attendance; age of last attendance; most regular attendance period.</i>
Drug use	<i>Lifetime and past 12 month drug use and frequency (licit drugs, illicit 'traditional' drugs, NPS); age of first use; age of last use; heaviest use period; where used most often; amount of ecstasy used; motivations for and intentions to future change at baseline; actual change and influences on change at follow-up; problematic alcohol and drug use (AUDIT-C; DUDIT).</i>
Risks and experiences	<i>Risk perception; positive and negative experiences following drug use at events; social acceptability of drug use; perception of how positive or negative impact of drug use; mood (WHO-5); depression (PHQ2); anxiety (GAD2).</i>
Harm reduction	<i>Endorsement of various harm reduction strategies before, during and after use.</i>

AUDIT-C – Alcohol Use Disorder Identification Test for Consumption; DUDIT – Drug Use Disorder Identification Test; WHO-5 – World Health Organisation 5; PHQ – Patient Health Questionnaire; GAD – Generalized Anxiety Disorder

1.5.2 Development

The items in the EMSS were derived from validated scales, previous literature and extensive discussions drawing on consortium members' wealth of experience of research and service provision in the fields of drug use, addiction, nightlife and harm reduction. The final list of items was professionally translated from English into each language (Dutch, Flemish, French, Italian and Swedish) then back-translated to English, and any inconsistencies with the original were adjusted accordingly to ensure that each question was being asked in the same way across all languages.

To ensure that survey content was relevant to young adults engaging with the nightlife scene, a focus group was held with regular club and festival goers. This resulted in a number of important changes, such as avoidance of the use of the term 'EDM' to refer to electronic dance music in general, as this was deemed quite a divisive term amongst this population. Furthermore, additional positive experiences and harm reduction strategies were suggested and incorporated into the final version of the survey. The final survey items can be found in Appendices 1 and 2.

The survey was built and hosted on Qualtrics, an online research platform. This afforded the opportunity of incorporating complex display logic so that participants were not shown irrelevant questions, for example about a drug they had never used. Furthermore, it was possible to create distribution lists so that participants were automatically emailed their unique link to the follow-up survey exactly 12 months after completion of baseline.

Ethical approval for the study was granted by the UCL Research Ethics Committee – project ID: 10437/001 (Appendix 3).

1.5.3 Recruitment

1.5.3.1 Participants

The target population for this study was young adults living in Europe who engaged regularly with the nightlife scene. As such, EMSS inclusion criteria were as follows:

1. Aged between 18 and 34;
2. Attended at least six electronic dance music events in the past 12 months;
3. Current resident in Belgium, Italy, the Netherlands, Sweden or the UK.

The age range was chosen so that the upper age limit matched the EMCDDA's definition of a young adult (e.g. EMCDDA, 2019). Electronic dance music was chosen as the focus as this scene has a large presence in all participating countries, while six events in the past 12 months was considered an appropriate cut-off both to ensure sufficient engagement and to capture variance in attendance frequency. Being resident in one of the five participating countries was chosen to enable the consortium to make between-country comparisons.

Incentives were offered to participants at baseline and follow-up to enhance recruitment and retention. Completers of the baseline survey were entered into a prize draw for three Apple Macbooks, three Apple iPads, three Boom Bluetooth speakers and 45 €20 gift

vouchers. A €20 gift vouchers was offered for completion of the follow-up survey, along with entry into a further prize-draw for six Macbooks, six iPads and fifteen Bluetooth speakers.

The EMSS employed both an online and offline method to recruit participants to the cohort. Protocols were written for each and followed by all countries to ensure the same methods were being used in all countries.

1.5.3.2 Methods – online recruitment

Online recruitment initially took the form of Facebook and Instagram adverts run from a central EMSS Facebook account. Facebook allows for adverts to be targeted at certain groups based on demographics, interests and interaction with other Facebook pages and websites. Resident Advisor (www.residentadvisor.net) is a website selling tickets for and reviewing electronic dance music events, and is widely used in each of the five participating countries. As such, interaction with the Resident Advisor website or Facebook page and the age range as per the inclusion criteria were selected as targeting information for the initial stage of online recruitment.

In an attempt to improve the rate of recruitment, targeted information was expanded to include a wide range of popular DJs, record labels, festivals, nightclubs and music genres. A number of websites and social media groups in each country were also contacted to promote the study, while articles were also written for national media outlets (e.g. Waldron, Grabski, Mokrysz, Freeman, & Measham, 2017; Appendix 4).

The most successful strategy, however, was the introduction of country specific social media adverts. These adverts were run from countries' institutional Facebook page ('UCL Clinical Psychopharmacology Unit' in the UK), and used different pictures with a more informal tone to the accompanying text and more explicit reference to the incentives on offer.

Completers of the baseline survey were sent an email containing their unique link for the follow-up exactly 12 months later. Participants were also sent a two week reminder, and a final reminder two weeks before the survey closed in November 2018.

1.5.3.3 Methods – offline recruitment

Offline recruitment occurred at nightclubs and festivals during the same period as online recruitment. A list of the top nightclubs in the largest and third largest city in each country was compiled using the ratings available on Resident Advisor, and verified with ‘nightlife experts’ to ensure important venues were not omitted. Nightlife experts were individuals heavily involved in the scene in each country, such as DJs, nightclub owners, welfare workers and event promoters. The decision to include the most popular venues was taken to ensure sufficient recruitment and to reach a broad range of participants. Furthermore, popular clubs were considered more likely to be comparable between countries than underground events.

Resident Advisor does not provide statistics on festivals, thus a list of key events was drawn up in consultation with each nightlife expert. The final lists of nightclubs and festivals were then randomised, and venues were contacted in order to explain the study, and for those who agreed, arrange access for recruitment. If a venue refused access, the next one on the list was contacted to try and reach each country’s target of four clubs per city and three festivals.

To reduce the risk of selection bias, participants were selected at nightclubs and festivals using a random intercept method, adapted from previous research (Graham et al., 2014). This required field-workers to stand at a fixed point and approach every second person who entered an imaginary zone covering an area large enough to experience steady foot traffic, and ask them to complete a short questionnaire asking for age, gender and past 12 month drug use and nightlife engagement (see Figure 1.1). Zones in crowded areas were approximately two by four meters, while in less dense areas zones were larger to ensure a regular flow of potential participants. Field-workers noted whether an individual had self-selected to complete the questionnaire so that these could later be discarded due to violation of the random sampling method. Additionally, field-workers marked questionnaires that were completed by individuals who were visibly intoxicated so these could also be discarded due to concerns about the ability to provide informed consent for participation. The number of people who refused to participate was also counted, so that

an overall response rate could be calculated. Participants were also given the URL for the online survey and encouraged to complete it at a later date.

1.5.3.4 Informed consent

Whether clicking on social media adverts or following the link given at nightclubs and festivals, all participants were first shown the EMSS Participant Information Sheet (Appendix 5). This described the benefits and possible risks of participation, and contained

Figure 1.1: Short offline questionnaire completed by individuals at clubs and festivals



How old are you? years

What is your gender? M F Other

Do you currently live in the UK? Yes No

How many times did you attend a dance/ electronic music event in the last 12 months times

410001

How often did you attend this event or venue in the last 12 months?

	3 times a week or more	Weekly	Fortnightly	Monthly	Every 2 or 3 months	3 times or less in the year	Not in the last 12 months
Nightclubs	<input type="checkbox"/>	<input type="checkbox"/>					
Illegal: festivals/outdoor parties/raves	<input type="checkbox"/>	<input type="checkbox"/>					
Licensed: festivals /outdoor parties/raves	<input type="checkbox"/>	<input type="checkbox"/>					
Pubs/bars	<input type="checkbox"/>	<input type="checkbox"/>					
House party/Party at a friend's house	<input type="checkbox"/>	<input type="checkbox"/>					

How often did you use these drugs in the last 12 months?

	3 times a week or more	Weekly	Fortnightly	Monthly	Every 2 or 3 months	3 times or less in the year	Not in the last 12 months
 Alcohol	<input type="checkbox"/>	<input type="checkbox"/>					
 Cannabis	<input type="checkbox"/>	<input type="checkbox"/>					
 Ecstasy/ MDMA	<input type="checkbox"/>	<input type="checkbox"/>					
 Cocaine	<input type="checkbox"/>	<input type="checkbox"/>					
 Amphetamines	<input type="checkbox"/>	<input type="checkbox"/>					

guarantees of anonymity and confidentiality with regard to data collection, storage, access and processing, as well as researcher contact information should there be further questions. In order to progress to the baseline EMSS, all participants were required to provide their informed consent stating that they had read and understood the Information Sheet, met the inclusion criteria and consented to being contacted by email about the follow-up survey.

1.5.3.5 Sample size

The original target was to recruit 2,000 eligible participants to the EMSS baseline survey in each country, with 1,500 recruited online and 500 offline, resulting in an overall sample size of 10,000. In total, 8,045 eligible participants completed the baseline survey, with 2,897 completing the 12 month follow-up, a response rate of 36.0% (see Table 1.2).

Table 1.2: EMSS sample size and response rate by country

Country	Baseline		Follow-up		Response rate %
	N	%	N	%	
Belgium	1345	16.7	495	17.1	36.8
Italy	1147	14.3	341	11.8	29.7
Netherlands	2123	26.4	840	29.0	39.6
Sweden	1371	17.0	498	17.2	36.3
UK	2059	25.6	723	24.9	35.1
Total	8045	100	2897	100	36.0

Despite the initial aim of recruiting 25% of the final sample via offline methods, the vast majority of survey respondents indicated that they heard about the survey online rather than at a club or festival, as displayed in Table 1.3. Unfortunately, no nightclubs or festivals in Sweden granted field-workers access for offline recruitment. However, 27 nightclubs across 45 different evenings and 19 festivals were visited in Belgium, Italy, the Netherlands and the UK, where 3,529 eligible offline questionnaires were collected at an overall response rate of 75.5%. However, despite being encouraged to later fill in the online survey, only 9.9% of these individuals (n=349) went on to do so.

Table 1.3: EMSS recruitment source by country

	Online adverts		At a club or festival		Word of mouth		Total N
	n	%	n	%	n	%	
Belgium	1274	94.72	49	3.64	22	1.64	1345
Italy	1043	90.94	34	2.96	70	6.10	1147
Netherlands	1892	89.12	192	9.04	39	1.84	2123
Sweden	1337	97.52	0	0.00	34	2.48	1371
UK	1944	94.42	74	3.59	41	1.99	2059
Total	7490	93.10	349	4.34	206	2.56	8045

NB 'Word of mouth' refers to those EMSS baseline completers who heard about the survey via friends or family, as opposed to directly via online adverts or offline at a club and festival

1.6 Additional ALAMA-Nightlife studies

In addition to the EMSS, the ALAMA-Nightlife product conducted three further studies: Ecological Momentary Assessment of polydrug use; verification of self-reported drug use using breath samples collected at festivals; and a contextual analysis of nightlife related content on social media. Of these, the UK team were only involved in the Ecological Momentary Assessment, and not the breath sampling study (Belgium and Sweden) or the contextual analysis (Italy and Belgium), and thus will be the only study discussed in this Chapter. A brief summary of the remaining two studies can be found on the EMSS website (<https://www.emssurvey.eu/projectinfo>).

1.6.1 Ecological Momentary Assessment (EMA) of drug use in nightlife settings

EMA is a methodology that assesses behaviours and characteristics in real time in participants natural environment. It is, therefore, an ideal method to investigate drug use patterns as they occur in nightlife settings, such as clubs and festivals. The ALAMA-Nightlife project therefore conducted an EMA study, led by our collaborators in the Netherlands, to determine real-time patterns and short term consequences of use, to complement longer term findings from the EMSS.

Participants were completers of the baseline EMSS resident in the Netherlands or the UK, who indicated use of ecstasy/MDMA on at least three occasions in the previous 12 months. In total 307 participants were recruited to the EMA study, with 164 living in the Netherlands and the remaining 143 in the UK.

Participants were instructed to download a custom built smartphone app, which sent surveys to participants to be completed in real-time over a five-week period in summer 2018. In order to capture short term patterns of use, intentions and consequences in the days after use, the EMA app sent out four types of survey:

1. Daily survey: Assessment of mood, drug use, sleep, concentration, memory and daily functioning in the past 24 hours. Sent 8pm every day for five weeks.
2. Thursday survey: Intentions to use alcohol and other drugs over the following weekend. Appended to the Daily survey every Thursday.
3. Night out survey: Assessment of alcohol and drug use in the moment (past 2 hours), current mood and social and physical environment. Sent Friday and Saturday 10pm, 12am, 2am and 4am if at a nightclub, or 3pm, 5pm, 7pm, 9pm if at a day festival.
4. Day after survey: Assessment of negative consequences and positive experiences of drug use in the past 24 hours. Sent Saturday and Sunday at 3pm.

Unfortunately data from the EMA study were not made available to the UK team in time for inclusion in this thesis. As such, this studies presented in this thesis utilise data solely from the EMSS.

1.7 Aims of this thesis

The overall aim of this thesis, in line with that of the ALAMA-Nightlife project, is to gain insight into contemporary drug use patterns amongst young adults regularly engaging with the European nightlife scene.

The specific questions that I aim to address in this thesis are:

1. Can the internet be successfully used to access a population of young adults regularly engaging with the European nightlife scene?
2. What are the different past 12 month drug use profiles amongst this population, and what are their associations with potentially harmful drug use and demographic characteristics?
3. How does the adoption of harm reduction strategies relate to past 12 month polydrug use, and to positive experiences and negative consequences associated with drug use?
4. What are the transitions in drug use over 12 months, and how are risk perception, nightlife engagement and demographic characteristics associated with an increase, decrease or maintenance of use?

The remaining chapters of this thesis outline studies conducted utilising EMSS data to answer each of these questions in turn. The final chapter then provides an overview and integrates findings from these empirical chapters, and discusses how they contribute to addressing the overall aim of the thesis. An overview of the size and description of the sample for each chapter is presented in Table 1.4.

Table 1.4: Sample size and description for each empirical chapter

	Study description	Sample size	Sample description
Chapter 2	Comparison of offline and online recruitment methodologies	9,682	Offline: Completers of a short questionnaire at nightclubs and festivals in Belgium, Italy, the Netherlands and the UK in 2017.
		<i>Offline = 3,529</i> <i>Online = 6,153</i>	Online: Completers of the EMSS baseline survey in 2017, resident in Belgium, Italy, the Netherlands or the UK, who were recruited to the survey via online advertising. EMSS completers who heard about the study at a festival or club (n=349) or via word of mouth (n=206), as opposed to online adverts, were excluded from the sample. No offline recruitment occurred in Sweden, thus online participants in Sweden (n=1,337) were also omitted from the online sample.
Chapter 3	Latent class analysis to determine cross-sectional past 12 month drug use profiles	8,045	All completers of the baseline EMSS survey in 2017 resident in Belgium, Italy, the Netherlands, Sweden or the UK. No restrictions on recruitment source or country of residence were applied.
Chapter 4	Latent class analysis to determine harm reduction patterns among polydrug users	4,196	Restricted to members of drug use profiles that were characterised by patterns of past 12 month polydrug use identified in Chapter 3.
			In total, 3,822 of 8,045 EMSS baseline completers belonged to one of two groups that were not characterised by polydrug use ('no illicit' or 'cannabis use' profiles), leaving 4,223 individuals defined by varying levels of polydrug use. Of these polydrug users, 27 individuals had missing harm reduction data, so were excluded from the sample.
Chapter 5	Latent transition analysis to determine longitudinal trajectories in drug use over 12 months	2,897	Completers of both the EMSS baseline survey in 2017 and the EMSS follow-up survey in 2018, resident in Belgium, Italy, the Netherlands, Sweden or the UK at baseline. No restrictions on recruitment source, country of residence or drug use were applied.

EMSS – Electronic Music Scene Survey

Chapter 2: How do online and offline sampling compare in a multinational study of drug use and nightlife behaviour?

The work presented in this chapter gave rise to the following publication:

Waldron, J., Grabski, M., Freeman, T.P., Mokrysz, C., Hindocha, C., Measham, F., van Beek, R., van der Pol, P., Hauspie, B., Dirkx, N., Schrooten, J., Elgán, T.H., Feltmann, K., Benedetti, E., Scalia Tomba, G., Fabi, F., Molinaro, S., Gripenberg, J., van Havere, T., van Laar, M. & Curran, H.V., (2020). How do online and offline sampling compare in a multinational study of drug use and nightlife behavior in Europe? *International Journal of Drug Policy*, 82, 102812

2.1 Introduction

As outlined in Chapter 1, ALAMA-Nightlife is a project investigating drug use amongst young adults engaging with the nightlife scene in five European countries: Belgium, Italy, Netherlands, Sweden and the UK. The core component of the project is the EMSS, an online survey examining drug use and nightlife behaviours.

There are a number of potential advantages to using online survey methods (Barratt, Potter, et al., 2015; Van Gelder, Bretveld, & Roeleveld, 2010), which have seen them being increasingly employed as a research tool. One such advantage is that online surveys allow researchers to access large numbers of participants at a lower cost than traditional methods such as face-to-face interviews or mailed surveys (Al-Salom & Miller, 2019; Barratt & Lenton, 2015; Miller, Johnston, Mcelwee, & Noble, 2007; Riva, Teruzzi, & Anolli, 2003). Furthermore, the internet has been successfully used to access hard to reach, or 'hidden', populations, such as those engaging in illegal or stigmatised behaviours (Barratt, Potter, et al., 2015; Potter et al., 2015; Ramo & Prochaska, 2012; Temple & Brown, 2012). As the internet can provide a greater degree of anonymity for participants disclosing potentially illegal or sensitive information, it is thought there is likely to be a reduction in suspicion or fears about disclosing drug use behaviours (Barratt, Ferris, & Lenton, 2015; Barratt, Potter,

et al., 2015; Kalogeraki, 2011; Miller & Sønderlund, 2010; Temple & Brown, 2012; Wardell, Rogers, Simms, Jackson, & Read, 2014).

Despite these advantages, there are potential limitations that should be considered when using the internet for research. The lack of interaction with participants potentially raises questions about whether the target population has actually been reached. Further, the external validity of online samples has also been questioned, and it has been argued that corroborating information is needed to generalise findings from internet-based studies to wider populations (Barratt, Ferris, et al., 2015; Barratt et al., 2017; Miller & Sønderlund, 2010).

There are, however, very few studies validating online samples of alcohol and/or drug users against samples collected using more traditional offline methods, and none amongst a population of young adults engaging with the nightlife scene. Past year and past month cannabis users completing the Global Drug Survey, a large annual online survey about drug use, have been found to be broadly representative in terms of age and gender of probability samples of cannabis users from national household surveys in Australia, the United States and Switzerland (Barratt et al., 2017).

An online sample of Australian ecstasy users was found to be comparable to a probability sample from a national survey with regard to demographics and drug use patterns, leading to conclusions that the internet can be successfully used to recruit ecstasy users (Miller, Johnston, Dunn, Fry, & Degenhardt, 2010). However, in a comparison between a different online sample of Australian ecstasy users and a later iteration of the same national survey, Barratt and colleagues (2015) found that the online sample were younger on average, had a higher proportion of males and were more likely to report polydrug use. Furthermore, a study comparing an online sample of cannabis cultivators with one from a national survey found that, while there were many similarities, the online sample were more likely to be male, younger, and not to have used cannabis before the age of 16 (Barratt & Lenton, 2015).

Previous evidence indicating that some online samples of drug users may differ from offline probability samples highlights the need to validate those recruited solely through the internet against those known to be the target population. Furthermore, additional limitations of online research, notably the purposive nature of sampling and the inability to calculate response rates prohibiting the estimation of prevalence in a population, make the

need to validate online samples even more important if findings are to be generalised to a wider population. However, to the authors' knowledge, this validation has never been done for an online sample of European adults engaging with the nightlife scene.

As such, the aim of this study was to compare an online survey sample to a venue-based offline sample randomly recruited at nightclubs and festivals with respect to demographics, drug use and nightlife engagement, and to estimate the magnitude of observed differences.

2.2 Methods

2.2.1 Design

This study was a survey validation comparing online convenience and random offline sampling. The online sample completed the baseline EMSS, an internet-based survey about their drug use and nightlife engagement. The offline sample completed a face-to-face questionnaire at nightclubs and festivals that contained a small subset of the questions asked of the online sample.

Ethical approval was granted by each countries' institutional ethics committees.

2.2.2 Participants

2.2.2.1 Recruitment

The online and offline recruitment strategies are described in detail in Chapter 1, therefore will only be briefly summarised here.

2.2.2.1.1 Online sample

The online sample was recruited between May and November 2017 using convenience sampling, primarily through paid, targeted advertising on the social media platforms Facebook and Instagram. Adverts were targeted at people who liked or interacted with content related to the nightlife scene, including a range of popular nightclubs, DJs, music genres, events and news groups in each country, and who were within the age range of our inclusion criteria (see below). Online groups, fora and websites focussing on electronic dance music were also contacted to advertise the survey. Survey completers were entered

into a prize draw for Macbooks, iPads and Bluetooth speakers as an incentive for participation.

2.2.2.1.2 Offline sample

The offline sample was recruited at nightclubs and festivals using a random intercept method during the same time period as the online sample. When at nightclubs and festivals, field-workers approached every second person entering an imaginary zone to complete a short offline questionnaire asking for demographics and past 12 month drug use and nightlife engagement. Field-workers noted those who self-selected in violation of the random sampling method, and those who were visibly intoxicated over concerns around informed consent. The total number of refusals were also counted.

Access to nightclubs and festivals could not be agreed in Sweden, thus no offline data were collected. Therefore this study compared the online and offline samples in Belgium, Italy, the Netherlands and the UK.

As field-workers informed and provided the EMSS survey link to offline participants, the online sample in this present study is restricted to those who indicated that they heard about the study online, rather than at a nightclub, a festival or by word of mouth.

2.2.2.2 Inclusion criteria

Inclusion criteria for participants in both the online and offline samples were: aged 18 to 34; having attended at least six electronic dance music events in the past 12 months; and residing in one of the participating countries.

The age range was chosen to match the upper age limit of the European Monitoring Centre for Drug and Drug Addiction's (EMCDDA) definition of a 'young adult' (e.g. EMCDDA, 2019), while the number of events was chosen to ensure sufficient engagement with the nightlife scene.

2.2.3 Measures

All participants were asked their age, gender, country of residence and the number of electronic dance music events attended in the past 12 months. Participants were also asked how frequently they used five drugs (alcohol; cannabis; ecstasy/MDMA; cocaine; amphetamines) and attended five venues (nightclubs; licensed festivals/raves; illegal festival/raves; pubs/bars; house-parties) in the past 12 months.

Offline participants were asked only these questions using a pen and paper questionnaire. Online participants answered these questions as part of the baseline EMSS.

2.2.4 Statistical analysis

2.2.4.1 Offline sample weighting

One consideration when using venue-based sampling methods is that the probability of being included in the study is related to the frequency that an individual attends such venues (Jenness et al., 2011; MacKellar et al., 2007). In line with previous studies using venue-based recruitment (F. Fernández-Calderón, Cleland, & Palamar, 2018; Palamar et al., 2019; Palamar, Le, & Cleland, 2018), a sample weight was created based on self-reported frequency of venue attendance to account for the offline sample's different relative selection probabilities. The proportion of days in the past 12 months that an individual attended a venue was calculated by dividing participants' responses to the question "How many times did you attend a dance/electronic dance music event in the past 12 months?" by 365. An individual's selection probability was then estimated by calculating the inverse of this proportion, thus up-weighting those with lower probabilities and down-weighting those with higher probabilities of being recruited to the offline sample.

Using the number of events attended in the past 12 months was deemed the most suitable metric from which to estimate venue-based selection probabilities for the offline sample. Online selection probabilities are likely to be influenced by levels of engagement with the internet rather than event attendance, for which no data were collected. As such, it was not possible to appropriately weight the online sample in this study.

2.2.4.2 Assessing sample differences

Differences in age between the online and weighted offline sample were assessed using ANOVA, while a chi-square test was performed to test for differences in gender. Multivariate logistic regression, adjusting for age, gender and country of residence, was used to compare the samples in terms of past 12 month drug use and venue attendance. In order to compare the samples' mean frequency of drug use and venue attendance, a series of linear regression models were fitted, also adjusting for age, gender and country of residence. All questions in the EMSS were forced responses, therefore there were no missing data for the online sample. However, some offline participants did not fill in all questions on the pen and paper questionnaire, and were therefore omitted from

corresponding analyses. Statistical significance was assessed using Bonferroni corrected p-values ($0.05 / 22 = 0.0023$) to account for multiple comparisons. All statistical tests were performed using IBM SPSS Statistics, version 25 (IBM Corp, 2017).

Cohen's *d* for differences in age and Cramer's *V* for differences in gender were calculated as effect size estimates, with a value of 0.10 taken to indicate a small effect, 0.30 a medium effect and 0.50 a large effect (Cohen, 1992). The magnitude of observed differences in past 12 month drug use and venue attendance were determined by adjusted odds ratios, while those for average use and attendance frequency were assessed by adjusted regression coefficients.

2.3 Results

2.3.1 Sample sizes

The numbers of online and offline participants living in Belgium, Italy, the Netherlands and the UK are displayed in Table 2.1. In total, 6153 eligible participants completed the EMSS baseline survey who indicated that they had heard about it online. The offline sample comprised of 3529 eligible participants recruited from 27 different nightclubs and 19 festivals, at an overall response rate of 75.51%. A greater number of festivals were attended than initially planned following difficulties with agreeing recruitment at nightclubs and lower rates of recruitment than anticipated. In total, 414 offline questionnaires were completed by individuals who self-selected or were invisibly intoxicated, thus were not included in the offline sample.

Table 2.1: Numbers of online and offline participants in each country

Country of residence	Online		Offline	
	N	% of sample	n	% of sample
Belgium	1274	20.71	642	18.19
Italy	1043	16.95	459	13.01
Netherlands	1892	30.75	1077	30.52
UK	1944	31.59	1351	38.28
TOTAL	6153	100	3529	100

2.3.2 Demographics

Online participants were on average approximately one year younger (mean 23.21 years) than offline participants (mean 24.42 years), with the effect size estimate showing this difference to be small ($F_{(1,9681)}=139.43, p<0.001, \text{Cohen's } d=0.24$). The online sample also had a lower proportion of women (female=30.29%; male=69.29%; other=0.44%) than the offline sample (female=40.85%, male=58.00%, other=1.15%; $\chi^2=133.38, p<0.001, \text{Cramer's } V=0.11$) with a small effect size estimate.

2.3.3 Drug use

The percentages of the online and weighted offline samples using each drug in the past 12 months are shown in Figure 2.1. While both samples followed the same pattern with regard to most (alcohol) to least (amphetamines) used drug, lower proportions were observed in the online than the weighted offline sample for all five. Results from multivariate logistic regressions are displayed in Table 2.2, and show that, after adjusting for age, gender and country of residence, the online sample were at significantly lower odds of having used all five drugs than the weighted offline sample, although the difference in alcohol use was short of significance at the Bonferroni corrected p-value.

Figure 2.1: Past 12 month drug use within online and weighted offline samples

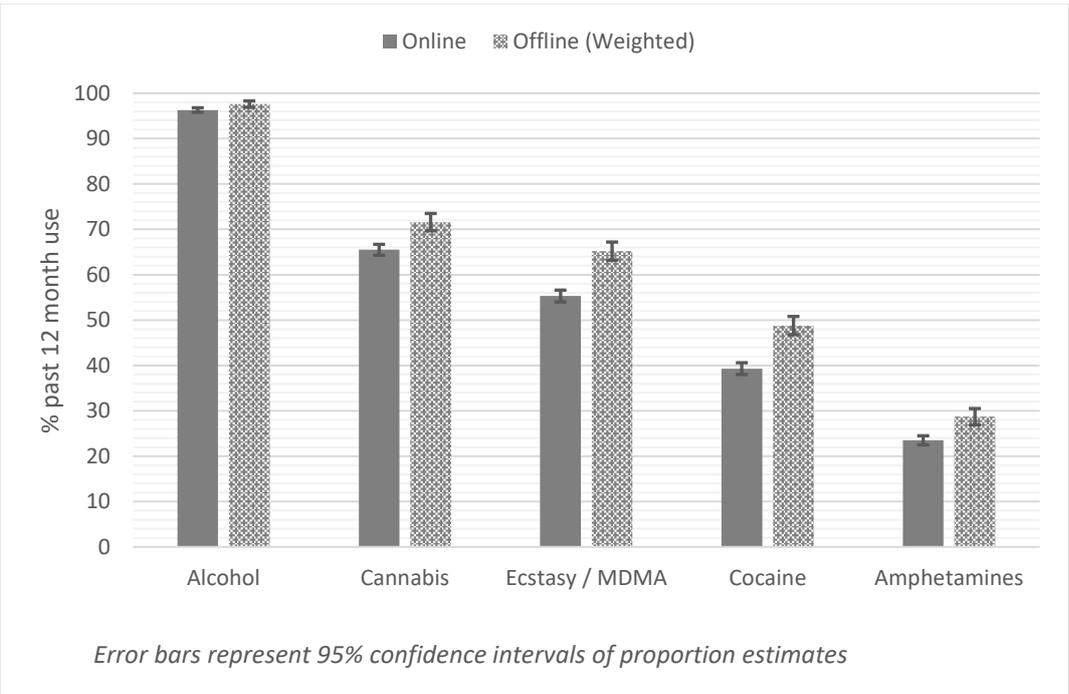


Table 2.2: Results from multivariate logistic regression comparing online sample with weighted offline sample with respect to past 12 month drug use and venue attendance, adjusting for age, gender and country of residence

	aOR ^a	(95% CI)	p
Past 12 month drug use			
Alcohol	0.66	(0.49, 0.90)	0.009 ^b
Cannabis	0.71	(0.64, 0.80)	<0.001
Ecstasy / MDMA	0.61	(0.55, 0.69)	<0.001
Cocaine	0.70	(0.63, 0.78)	<0.001
Amphetamines	0.68	(0.60, 0.76)	<0.001
Past 12 month venue attendance			
Nightclubs	1.39	(1.14, 1.70)	<0.001
Licensed festivals / raves	0.96	(0.77, 1.18)	0.68
Illegal festivals / raves	0.66	(0.60, 0.73)	<0.001
Pubs / bars	0.37	(0.29, 0.47)	<0.001
House-parties	0.59	(0.50, 0.70)	<0.001

^aOffline sample set as reference
^bNon-significant at Bonferroni corrected significance level (p = 0.0023)
aOR – adjusted odds ratio, adjusting for age, gender and country of residence; 95% CI – 95% confidence interval for adjusted odds ratio

Figure 2.2 displays the mean use frequencies of each drug by both samples. Both samples again showed the same pattern with respect to most to least frequently used, with the online sample using each drug on average less frequently than the weighted offline sample. Multivariate linear regression coefficients (Table 2.3) suggest that, after adjusting for demographic traits, the online sample was associated with a mean frequency score of less than one point lower than the weighted offline sample for each drug.

Figure 2.2: Mean past 12 month drug use frequency within online and weighted offline samples

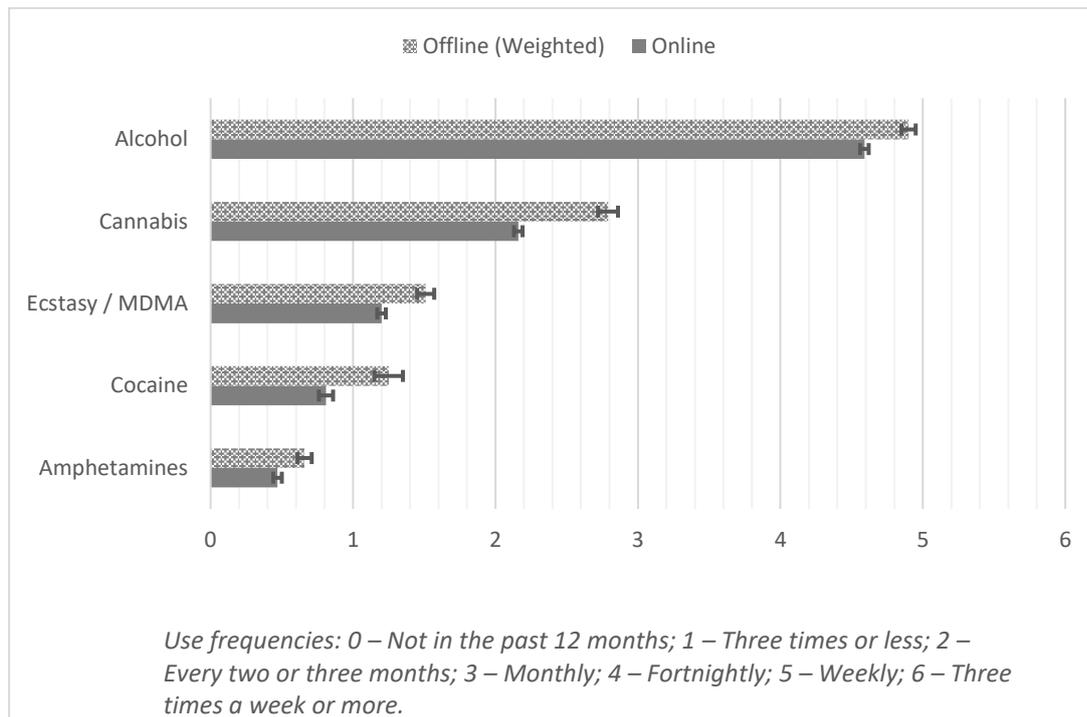


Table 2.3: Results from multivariate linear regressions comparing online sample with weighted offline sample with respect to past 12 month drug use and venue attendance frequency, adjusting for age, gender and country of residence

	B ^a	(95% CI)	p
Past 12 month drug use			
Alcohol	-0.29	(-0.36, -0.23)	<0.001
Cannabis	-0.74	(-0.85, -0.63)	<0.001
Ecstasy / MDMA	-0.31	(-0.37, -0.25)	<0.001
Cocaine	-0.40	(-0.49, -0.33)	<0.001
Amphetamines	-0.23	(-0.28, -0.17)	<0.001
Past 12 month venue attendance			
Nightclubs	0.07	(0.001, 0.14)	0.05 ^b
Licensed festivals / raves	-0.24	(-0.30, -0.18)	<0.001
Illegal festivals / raves	-0.26	(-0.32, -0.20)	<0.001
Pubs / bars	-0.42	(-0.50, -0.35)	<0.001
House-parties	-0.84	(-0.91, -0.76)	<0.001

^aOffline sample set as reference

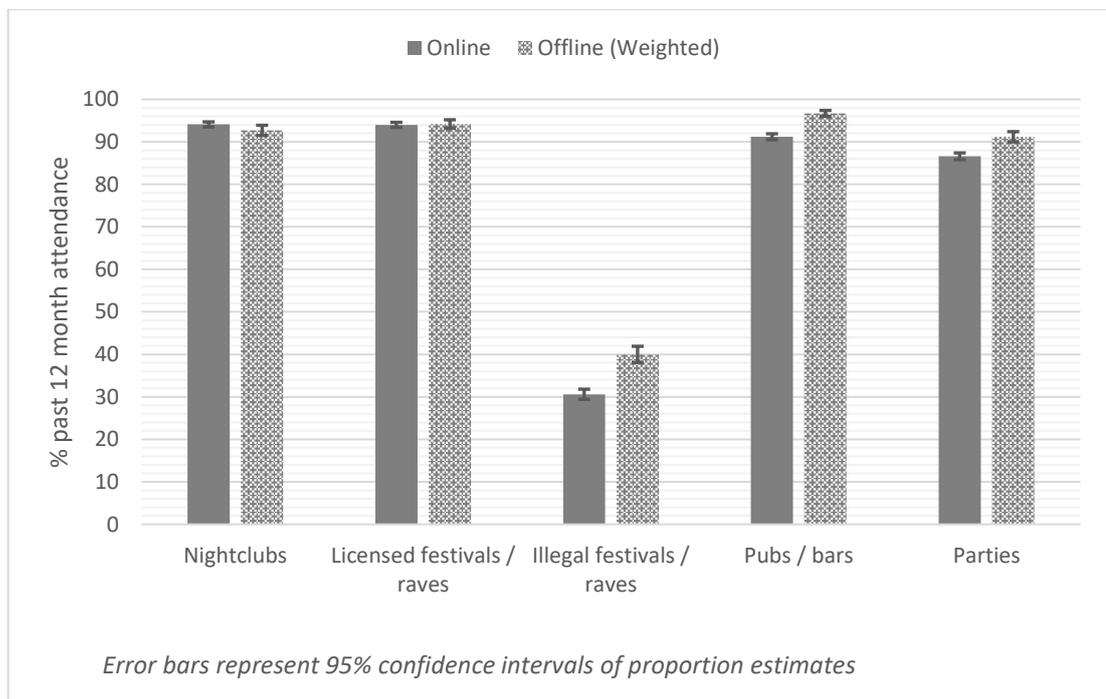
^bNon-significant at Bonferroni corrected significance level (p = 0.0023)

B – linear regression coefficient, gender and country of residence; 95% CI – 95% confidence interval for regression coefficient

2.3.4 Nightlife engagement

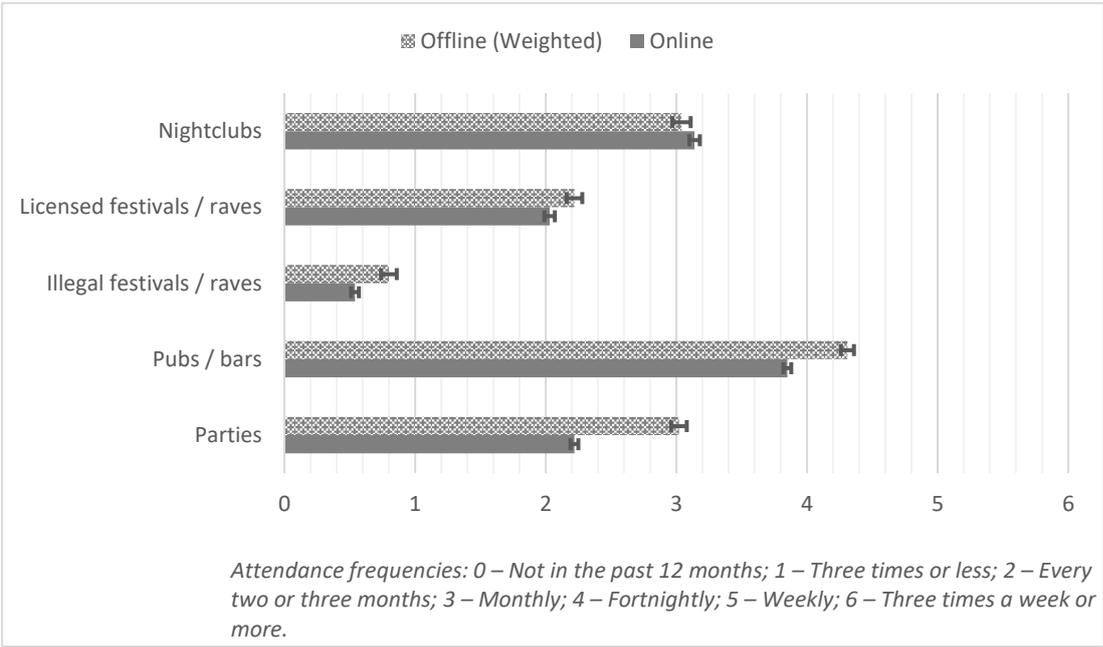
Figure 2.3 shows the proportions of both samples that attended each venue in the past 12 months, while adjusted odds ratios are displayed in Table 2.2. No difference was observed between the two samples with respect to past year attendance at licensed festivals. The online sample had lower odds of having attended illegal festivals, pubs and house-parties, and higher odds of having attended nightclubs than the weighted offline sample.

Figure 2.3: Past 12 month venue attendance within online and offline weighted samples



The mean attendance frequencies for each sample are shown in Figure 2.4. As with drug use frequency, the two samples showed the same pattern in terms of the order of most to least frequently attended venue. When adjusting for demographic characteristics, no differences were observed between the two samples in terms of frequency of attendance at nightclubs. For the remaining four venues, the offline sample was associated with significantly lower mean attendance frequencies, with the largest difference observed for house-parties. The regression coefficients (Table 2.3) indicate that observed differences were less than one point on a seven point scale.

Figure 2.4: Mean past 12 month venue attendance frequency within online and weighted offline samples



2.3.5 Effect of weighting the offline sample on drug use estimates

Unweighted and weighted estimates for the past 12 month use and average frequency of use of each drug for the offline sample are shown in Table 2.4. Weighting the offline sample based on the number of events attended in the past 12 months attenuated the estimates of past 12 month use and average frequency of use of all five drugs. The influence of weighting was more pronounced for ecstasy/MDMA, cocaine and amphetamines, for which the confidence intervals of the weighted past 12 month use and average frequencies did not overlap those of the unweighted estimates.

Table 2.4: Effect of weighting on offline sample’s estimates of drug use

Past 12 month drug use	Unweighted estimates		Weighted estimates	
	%	(95% CI)	%	(95% CI)
Alcohol	97.68	(97.18, 98.18)	97.58	(96.88, 98.13)
Cannabis	74.23	(72.76, 75.71)	71.63	(69.75, 73.43)
Ecstasy / MDMA	71.45	(69.94, 72.97)	65.25	(63.25, 67.25)
Cocaine	55.71	(54.01, 57.41)	48.78	(46.74, 50.82)
Amphetamines	34.26	(32.63, 35.89)	28.67	(26.93, 30.48)

Drug use frequency	Unweighted estimates		Weighted estimates	
	Mean	(95% CI)	Mean	(95% CI)
Alcohol	4.98	(4.94, 5.02)	4.90	(4.85, 4.95)
Cannabis	2.97	(2.89, 3.05)	2.79	(2.70, 2.89)
Ecstasy / MDMA	1.78	(1.73, 1.83)	1.51	(1.45, 1.57)
Cocaine	1.50	(1.44, 1.56)	1.25	(1.18, 1.31)
Amphetamines	0.84	(0.79, 0.89)	0.66	(0.61, 0.70)

2.4 Discussion

The aim of this study was to compare an online sample of young European adults engaging with the nightlife scene to a randomly recruited offline sample, and to estimate the magnitude of observed differences. Online participants were approximately one year younger on average and had a lower proportion of women than the weighted offline sample, with effect size estimates showing these differences to be small. Although both samples followed the same pattern in terms of most to least used drug in the past 12 months (alcohol, cannabis, ecstasy/MDMA, cocaine then amphetamines), the online sample had lower odds of having used each drug when adjusting for socio-demographic differences. However, upper bound limits of the 95% confidence intervals approached 1, indicating these differences may be small. The online sample also used each drug less frequently on average than the weighted offline sample, although adjusted regression coefficients indicate these differences were less than one point on a seven-point scale for all drugs, and less than half a point for all but cannabis.

No differences were found between the samples for past 12 month attendance at licensed festivals. The online sample were found to have higher odds of having attended a nightclub, but lower odds than the weighted offline sample for past 12 month attendance at illegal festivals, pubs and house-parties. While no differences between the samples with respect to the frequency of nightclub attendance were observed, the online sample had lower mean attendance frequencies for the remaining four venues. As with drug frequencies, adjusted regression coefficients suggest that the magnitude of these differences were less than one point on a seven point scale.

To the authors' knowledge, this is the first validation of an online sample of young adult substance users engaging with the European nightlife scene. Despite finding significant differences with regard to demographics, drug use and nightlife participation, adjusted odds ratios and regression coefficients suggest the magnitude of these to be small. These findings, therefore, suggest that online sampling shows good representativeness of young adults engaging with the nightlife scene.

These findings support previous studies that show the internet can be successfully used to access hidden populations of drug users (Barratt et al., 2017; Barratt & Lenton, 2015; Callas, Solomon, Hughes, & Livingston, 2010; Miller et al., 2010). However, that differences were observed between the online and weighted offline sample highlights the importance of validating online samples against one known to be the target population.

However, it must be noted that there are also limitations inherent with venue-based, offline recruitment. As discussed above, offline recruitment is likely to oversample more frequent nightlife goers and thus accounting for this using sampling weights as in this study is of high importance. However, such weights are based on informed estimates and thus establishing the perfect framework to account for this limitation is likely to be impossible. Furthermore, it is likely that willingness to engage with onsite fieldworkers will be higher for users of certain drugs than for others, thus potentially introducing bias based on drug use typology. For instance, participants under the influence of drugs known to promote prosocial effects such as cocaine and ecstasy/MDMA might arguably be more willing to engage in conversations and therefore participate in offline studies than those with more dissociative effects, such as ketamine. While the offline protocol for the present study excluded participants who were visibly intoxicated to mitigate this potential bias, it cannot be ruled out that a degree of intoxication went undetected by fieldworkers, and may indeed not be possible to detect by visual confirmation alone. It must also be considered that offline methodologies are far more time consuming and expensive than online methods. Given these limitations, the use of offline samples for validating online samples may only be necessary for populations where this has not yet been conducted in order to establish that both methods reach broadly similar groups of people with regards to traits of interest.

Contrary to research suggesting the use of the internet may prompt a greater degree of self-disclosure (Al-Salom & Miller, 2019; Miller & Sønderslund, 2010; Wardell et al., 2014), our online sample reported lower rates of and less frequent drug use than our offline

sample. It is possible this was due in part to our differing methods of data collection. Online participants provided an email address to be contacted for 12 month follow-up, whereas the offline sample were not asked to provide any identifying information on the pen-and-paper questionnaire. Despite guarantees of anonymity in that survey responses were never linked to email addresses and that IP addresses were not collected, this may have led to online participants feeling less anonymous in disclosing illegal behaviours than offline participants.

Beyond confirming that the target population has been reached, estimating the magnitude of differences between the two samples provides an opportunity to assess differences in sampling methods. Such differences can be useful for interpreting and adjusting estimates based on online and offline recruitment methods. Using estimates of the magnitude of differences is also important studies with large samples such as this, as even apparently trivial differences between the groups can reach statistical significance.

In addition to providing a way to account for the differing probabilities of offline selection when making comparisons with the online sample, the influence of weighting the offline sample on estimates of past 12 month drug use and average use frequency is an interesting standalone finding. Down weighting offline participants who attended more events in the past 12 months had the effect of lowering all estimates of past 12 month use and average use frequency of alcohol, cannabis, ecstasy/MDMA, cocaine and amphetamines. This further adds to the evidence from previous studies (e.g. Smirnov et al., 2013) that more frequent attendance at electronic dance music events is associated with higher levels of drug use. Interestingly, the effect of weighting was most pronounced for ecstasy/MDMA, cocaine and amphetamines, suggesting that the use of these drugs may be more strongly associated with engagement with the electronic dance music scene than the use of alcohol or cannabis.

2.4.1 Strengths and limitations

The key strengths of this study include the large sample size, the multinational design and the use of a venue-based random intercept method to recruit the offline sample. However, one limitation is that the offline sample were not asked about their use of drugs other than alcohol, cannabis, ecstasy/MDMA, cocaine or amphetamines. Similarly, additional demographic information such as sexual orientation and education that were included in the online survey were not asked of offline participants. However, the decision to limit the

number of questions in the offline questionnaire was advantageous in maximising the number of randomly selected people who agreed to participate.

Although weighting the offline sample in analyses was a strength of the study, the calculation of an individual's selection probability was limited to the number of self-reported events attended in the past 12 months. Other factors, such as the probability that an individual will be approached and how likely they are to agree to participate also influence the probability of selection (Jenness et al., 2011), which other studies weighting venue-based samples have utilised (Palamar et al., 2019; Palamar et al., 2018). However, accounting for this using sample weights requires an estimate of the number of eligible participants that were at a venue on all recruitment occasions, which are not available for our sample as capacity was not recorded in order to guarantee anonymity of venues. This also meant that the potential clustering effects of venues could not be accounted for in analyses.

Another limitation is that while we were able to estimate the differing probabilities in selection inherent to venue based sampling to weight our offline sample, no such data were available to do so for the online sample. It is likely that an individual's likelihood of responding to an online survey would be influenced by their level of engagement with the internet, such as the number of hours spent online or their propensity to respond to targeted advertising. No such data were collected in this study, thus we were unable to estimate and account for differing probabilities of selection and weight our online sample accordingly. Future studies might consider investigating measures that could be used to estimate online selection probabilities to compliment those existing for more traditional recruitment methods.

Furthermore, our results cannot be extended to other nightlife scenes beyond electronic dance music, nor to underground scenes.

2.4.2 Conclusion

In the first validation of an online sample of young adult substance users engaging with the European nightlife scene, small differences were observed with regard to age, gender, drug use and nightlife engagement when compared to an offline sample randomly recruited at clubs and festivals. These findings show that the internet can be used to access substance users engaging with the European nightlife scene, while highlighting the importance of validating online samples through comparison with a sample known to be the study target

population when such comparisons have yet to be performed. These findings may also prove useful for interpreting and adjusting estimates based on online and offline recruitment methods.

Chapter 3: Polydrug use profiles among young adults regularly attending the European nightlife scene – a multi country latent class analysis

3.1 Introduction

Those engaging with the nightlife scene long been associated with elevated rates of both licit and illicit drug use in comparison to use by the general population (Calafat et al., 2008; Fernandez-Calderón, Lozano-Rojas, & Rojas-Tejada, 2013; McCambridge et al., 2005; Van Havere, Vanderplasschen, Lammertyn, Broekaert, & Bellis, 2011; Winstock et al., 2001). Furthermore, polydrug use, the use of more than one substance at the same time or within a given time period (Connor et al., 2014; Martin, 2008), is also common amongst nightlife attendees, particularly in the electronic dance music scene (F. Fernández-Calderón et al., 2014; Grov et al., 2009; Winstock et al., 2001). In comparison to use of a single substance, polydrug use has been associated with increased risk of experiencing physical and psychological harm (Baggio, Studer, Mohler-Kuo, et al., 2014; F. Fernández-Calderón et al., 2014; Verdejo-García et al., 2010). It is, therefore, vital to gain an understanding of different polydrug use patterns amongst this population in order to identify those most at risk and to inform treatment and prevention interventions.

Latent class analysis (LCA) is a statistical method that identifies subgroups, or classes, of individuals within a population by grouping them on their probability of endorsing particular attributes or behaviours, such as drug use. LCA studies investigating polydrug use in nationally representative samples typically identify groups of users that differ solely in terms of the number of drugs used over a given timeframe (Armour, Shorter, Elhai, Elklit, & Christoffersen, 2014; Carter et al., 2013; Smith et al., 2011; Tomczyk, Hanewinkel, & Isensee, 2015). For example, using data from a probability survey of the general population of Great Britain, Carter et al (2013) identified three subgroups based on past 12 month use of eight different substances: a low use group defined by minimal alcohol and cannabis use; a group with moderate probabilities of alcohol, tobacco and cannabis use; and finally a high using group with moderate to high probabilities of endorsing past 12 month use of alcohol, tobacco, cocaine, ecstasy and cannabis. Similarly, Smith et al (2011) identified three classes

labeled “Mild/no drug use”, “Moderate range polydrug use” and “Wide range polydrug use” in an earlier iteration of the same survey.

Such subgroups defined by additive patterns of drug use have also been identified in a nationally representative sample of Danish young adults (Armour et al., 2014) and German adolescents (Tomczyk et al., 2015). Given the relatively low prevalence of drug use in general population samples, they may not be best placed to identify more nuanced patterns of polydrug use (Morley et al., 2015). However, a study using a probability sample of young Australian adults found five different classes that were not solely defined by an additive pattern of drug use, but additionally by the use of different combinations of drugs (Quek et al., 2013). To reflect which drugs were likely to have been used in the past 12 months, the authors labelled the identified subgroups as “Alcohol only”, “Alcohol and tobacco”, “Cannabis, ecstasy and licit drug use”, “Cannabis, amphetamines and licit drug use” and “Sedative and alcohol”. Additionally, when examining classes of individuals with drug abuse and dependence in a nationally representative sample of adults living in the USA, Agrawal and colleagues (2007) characterized classes as “No abuse/dependence”, “Cannabis”, “Stimulants and hallucinogens”, “Prescription drugs” and “High polysubstance”.

These findings, together with findings from LCA studies on therapeutic communities in Spain (D. Fernández-Calderón, Fernández, Ruiz-Curado, Verdejo-García, & Lozano, 2015) and Australian twins (Lynskey et al., 2006), suggest that there is considerable heterogeneity with regard to polydrug use beyond simply an additive model. It could, therefore, be that populations in which the prevalence of drug use is higher than the general population may be better suited to studies aimed at understanding more precise patterns of polydrug use. The Global Drug Survey (GDS) is an annual online survey into drug use whose self-selecting sample is acknowledged as having higher rates of drug use than wider populations (Barratt et al., 2017). Using data from GDS 2013, Morley et al (2015) identified six classes characterized by varying probabilities of having used eight different illicit and prescription drugs in the past 12 months (“Non polysubstance”; “Cannabis and ecstasy”; “Illicit only”, “Ecstasy and cocaine”; “Cannabis and medication”; “All substances”). Beyond identification of these different subgroups, the authors noted that the groups were primarily distinguished by differences in their use of ketamine, nitrous oxide, benzodiazepines and prescription opioids, differences which are generally not captured in LCA studies using probability samples (Morley et al., 2015).

Despite increased rates of drug use amongst those engaging with the nightlife scene, the author is only aware of four LCA studies that have utilised this population to investigate patterns of polydrug use (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017; Ramo et al., 2010; Sanudo, Andreoni, & Sanchez, 2015). Ramo et al (2010) used time-space sampling to recruit 400 18 to 29 year olds to investigate patterns of past 4 month use of MDMA, cocaine, ketamine, GHB, methamphetamine and LSD. Three classes were found, which reflected an additive pattern of polysubstance use: “Primary cocaine” (41.5%, high probability of having used cocaine); “Mainstream users” (44.3%, high probability of having used cocaine and MDMA); and “Wide range” (14.2%, high probability of having used cocaine, MDMA, ketamine and methamphetamine). Classes differentiated by use of an increasing number of drugs were also found in a study of past 12 month drug use (tobacco, cannabis, cocaine, ecstasy, inhalants, ketamine and hallucinogens) amongst 2420 nightclub patrons in São Paulo (Sanudo et al., 2015). The authors identified “No polydrug use” (55.0%), “Moderate polydrug use” (35.0%) and “High polydrug use” (10.0%) classes, with cannabis and tobacco use distinguishing moderate users from non-users, and use of all other drugs classifying users as high rather than moderate.

However, results from other studies suggest that polydrug use in nightlife populations is more heterogeneous and nuanced. One study (F. Fernández-Calderón et al., 2018) into the past 12 month drug use of 1045 nightclub patrons in New York City identified four classes of polysubstance use. In addition to non-polydrug using (61.1%) and extensive polydrug using (19.2%) classes, the authors found two moderate polydrug using classes. One moderate class was characterized by the use of stimulants (cocaine and amphetamines; 12.8%), and the other by the use of hallucinogens (LSD and magic mushrooms; 6.6%). Additionally, the moderate stimulant group also had higher rates of benzodiazepine and cannabis use, which the authors highlight may represent a group that would benefit from tailored harm reduction advice, for example warning about the dangers of combining depressants and stimulants (F. Fernández-Calderón et al., 2018).

To the author’s knowledge, only one such study has been conducted in the European nightlife scene. Using data collected from 1571 individuals attending electronic dance music events in Munich, Hannemann and colleagues (2017) also found a non-polydrug, cannabis using only class (“Conservative”; 34.9%) and an extensive using class with high probabilities of endorsing each drug, with the exception of heroin (“Unselective”; 10.9%). Furthermore, a class with high probabilities of endorsing use of LSD and magic mushrooms

("Psychedelic"; 17.5%) was identified, along with a further class characterized by high probabilities of endorsing ecstasy/MDMA, speed and cocaine ("Traditional"; 36.6%). As the largest observed classes were the "Conservative" and "Traditional" classes, the authors suggested that harm reduction focusing on the potential harms of cannabis use may be sufficient for a sizeable proportion of nightlife attendees, while others may benefit from drug testing facilities (Hannemann et al., 2017).

Distinguishing heterogeneous patterns of polydrug use among regular nightlife attendees affords the opportunity to identify those who might be most at risk of drug related harm, and to tailor appropriate prevention, treatment and harm reduction strategies accordingly. Furthermore, LCA can be extended to examine factors and outcomes that might be associated with particular subgroups. For example, in line with findings from nationally representative samples (Carter et al., 2013; Quek et al., 2013; Smith et al., 2011), Sanudo et al (2015) found that membership of the Moderate and High polydrug using classes was associated with younger age and being male. However, other studies in nightlife populations have found no relation between age and class membership (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017), while Fernández-Calderón and colleagues (2018) observed the highest proportion of women in the Non-polysubstance and Moderate polysubstance/stimulants classes, suggesting that the relationship between gender and polysubstance use may be more complex.

There is conflicting evidence regarding the association between education and polydrug use amongst nightlife populations. No relationship between class membership and highest level of education was found amongst a sample of nightclub patrons in São Paulo, with approximately a third of members in each class having obtained a university degree or higher (Sanudo et al., 2015). Ramo et al (2010), however, noted that an increase in polydrug use was significantly associated with lower levels of education in that the highest proportion of those having a university degree was observed in the "Primary cocaine" class (56.6%), and the lowest in "Wide range polydrug use" class (33.3%). Conversely, a later study conducted in the same city (F. Fernández-Calderón et al., 2018) found that a lower proportion of members of the "No polysubstance use" class held a university degree in comparison to all three polydrug using classes, and that of these the highest proportion was found in the "Moderate polysubstance use – stimulants" class (67.1%). The relationship between education and subgroups of polydrug users is yet to be explored in a European nightlife population.

The link between mental health and polydrug use profiles remains an underexplored area. An association between depressive symptoms and differing polydrug use subgroups in an Australian probability sample was found by Quek et al (2013), with both the “Cannabis, amphetamine derivatives and licit” and “Sedatives and alcohol” having significantly higher scores on the Kessler Psychological Distress Scale than the “Alcohol only” class. In a sample of Australian twins, polydrug use was found to be associated with poorer mental health, in that all four polydrug use classes had elevated rates on all indices (conduct disorder; social anxiety; major depressive disorder; suicidal ideation; suicide attempt) than the “Low use” class (Lynskey et al., 2006). Furthermore, while Morley et al (2015) found no differences with regard to depression, membership of the “Cannabis and medication” class was significantly associated with higher odds of having a self-reported diagnosis of anxiety. None of the four studies using LCA in nightlife populations (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017; Ramo et al., 2010; Sanudo et al., 2015) explored relationships between class membership and mental health outcomes, which warrants investigation given findings in other samples.

Similarly, there is a lack of evidence concerning how problematic drug and alcohol use might vary by differing polydrug subgroups in those regularly engaging with nightlife. Using a modified version of the Composite International Diagnostic Interview (CIDI), Ramo and colleagues (2010) indexed dependence on six ‘club drugs’ (MDMA, ketamine, GHB, methamphetamine, cocaine, LSD), and compared differences between the three classes of polydrug use they identified. High rates of dependence, defined as endorsing three or more CIDI items, were observed in the sample as a whole (63.5%), with a higher proportion of members of the “Wide range” class more likely to exhibit symptoms of dependence (89.5%), than either the “Primary cocaine” (59.0%) or “Mainstream” (59.3%) users (Ramo et al., 2010). No study, however, has investigated how different patterns of drug use as assessed using LCA are associated with problematic drug use in general, which is an important gap in the literature as polydrug use may result in problems beyond dependence.

No study has investigated differences between latent classes identified among those regularly engaging with nightlife with regard to problematic alcohol use. In two nationally representative studies that both identified three latent classes defining polydrug use as additive (Armour et al., 2014; Smith et al., 2011), increasing levels of use were associated with increased odds for hazardous drinking (Smith et al., 2011) and an increase of alcohol related problems (Armour et al., 2014). These findings echo those of an earlier study

(Lynskey et al., 2006) which found that alcohol dependence was more likely in all substance using classes compared to a non-using class, with the highest rates observed in the class defined by the highest levels of polydrug use. However, Morely et al (2015) found no differences between classes in terms of the odds of hazardous drinking, as indexed by the Alcohol Use Disorders Identification Test (AUDIT).

Given inconsistent evidence and gaps in the LCA literature amongst nightlife populations, an understanding of contemporary patterns of past 12 month polydrug use in the European nightlife scene is necessary to identify subgroups who might be at most risk of harm. As such, this study has three specific aims:

1. Identify profiles of polydrug use based on past 12 month use in a sample of young European adults engaging with the nightlife scene living in Belgium, Italy, Netherlands, Sweden and the UK.
2. Assess the discriminant validity of identified profiles by comparing socio-demographic characteristics.
3. Investigate the relationship between different profiles of past 12 month polydrug use and individuals' wellbeing, and their problematic alcohol and drug use.

3.2 Methods

3.2.1 Participants

The Electronic Music Scene Survey (EMSS) was an online survey investigating drug use in the nightlife scene in the Belgium, Italy, Netherlands, Sweden and the UK. Recruited through social media advertising, participants were aged 18 to 34, attended at least six electronic dance music events in the past 12 months and were resident in one of the participating countries. The sample for this study comprised 8,045 participants who completed the baseline survey in spring/summer 2017. For a detailed discussion of the survey development, recruitment strategy and methodology, see Chapter 1.

Each country sought ethical approval from their institutional ethics board. Ethical approval in the UK was granted by the UCL Research Ethics Committee (Project ID: 10437/001).

3.2.2 Measures

3.2.2.1 Drug use

Participants were shown a list of 22 licit and illicit drugs and asked to select which they had used in their lifetime. For each selected, participants were asked how often, if at all, they used that drug in the past 12 months. These frequency questions were collapsed into binary variables indicating past 12 month use of each drug, with responses 'Never' coded as 0, and all other responses coded as 1.

When examining the data, far higher rates of 3,4-Methylenedioxyamphetamine (MDA) use were observed at baseline than expected, with up to 8% of the sample in each country endorsing past 12 month use. At follow-up, past 12 month use was less than 1% in all countries, more in line with the expectations of the ALAMA Consortium. No errors in data coding or capture were found, but one key difference in the formatting of the drug use question was thought to possibly explain this discrepancy. Specifically, at baseline, MDA was displayed near the top of the list and crucially above MDMA, whereas at follow-up MDA was below MDMA. As such, it was thought that the much higher rates at baseline may in part be due to people mistaking MDA for MDMA, given the unfortunate similarity between the names of the two drugs. Therefore, MDA was omitted from all analyses presented herein due to concerns about the reliability of baseline responses.

3.2.2.2 Demographic characteristics

Age and the number of events attended in the past 12 months were collected as continuous variables. 'Implausible' answers to the number of events (that is, answers over 365) were recoded as missing and excluded from analyses. Gender (Male; Female; Other) and country of residence (Belgium; Italy; Netherlands; Sweden; UK) were forced, single-response items. Participants were asked whether they had completed, were currently attending or had never started four different levels of education equivalent across all five countries. A categorical variable indicating the highest level of educational attainment was created from the highest level that each participant reported having completed.

3.2.2.3 Well-being

Wellbeing was measured using the World Health Organisation – Five Well-Being Index (WHO-5) (Topp, Østergaard, Søndergaard, & Bech, 2015; WHO, 1998). The WHO-5 consists of five statements that relate to well-being in the last two weeks to which participants

respond either: All of the time (5); Most of the time (4); More than half the time (3); Less than half the time (2); Some of the time (1); At no time (0). The final score of 25 is then multiplied by 4 to give a final score ranging from 0 to 100, with a score of 0 being the worst and 100 the best imaginable in terms of well-being.

3.2.2.4 Problematic alcohol use

The Alcohol Use Disorders Identification Toolkit Consumption (AUDIT-C) (Bush, Kivlahan, McDonell, Fihn, & Bradley, 1998) was used as an index of problematic alcohol consumption. The AUDIT-C is a three item measure of frequency and quantity of alcohol consumption. Each item is scored from 0 to 4 and summed to give a total score out of 12, with higher scores indicating more hazardous alcohol consumption.

3.2.2.5 Problematic drug use

Potentially problematic drug use was assessed using the Drug Use Disorders Identification Test (DUDIT) (Berman, Bergman, Palmstierna, & Schlyter, 2005). The DUDIT is an eleven item measure covering frequency of drug use, drug dependence symptoms and drug related problems. Nine of the items are scored on 5 point scales ranging from 0 to 4, while two items are scored on a three point scale (0; 2; 4). Scores are summed to give a total ranging from 0 to 44, with higher scores indicating more severe drug use problems. Participants were asked to consider each item in relation to their overall drug use in the past 12 months, rather than to a specific substance.

3.2.3 Statistical analysis

3.2.3.1 Latent Class Analysis (LCA)

LCA was conducted to identify different profiles of substance users engaging with the nightlife scene in Europe, based on participants' past 12 month drug use. LCA uses the responses to a set of observed indicator variables to identify hidden subgroups of people that are similar to each other with respect to those observed variables (Lanza, Coffman, & Xu, 2013; Lanza & Rhoades, 2013; Nylund-Gibson & Choi, 2018). While conceptually similar to methods such as factor analysis, rather than grouping similar items, LCA groups people, thus it is thought of as a person-centred approach (Collins & Lanza, 2009; Nylund-Gibson & Choi, 2018). Two parameters of interest emerge from LCA. As individuals are classified into mutually exclusive classes, models are firstly inspected with regard to the relative sample size of each identified class. Secondly, conditional item probabilities are interpreted, which

show the probability that an individual in a given class endorsed each of the indicator variables, in this case past 12 month drug use (Nylund-Gibson & Choi, 2018).

To determine the model that best fits the data, that is, the one with the optimum number of classes, a series of models postulating an increasing number of classes are sequentially fitted and examined in turn. While there is no single statistical test to determine the best fitting model, a range of fit indices and likelihood ratio tests are examined to find converging evidence for the most parsimonious solution (Masyn, 2013; G. B. Morgan, 2015; Nylund, Asparouhov, & Muthén, 2007). In practice it is not uncommon that fit indices do not support the same solution, thus an important consideration in model enumeration is the substantive interpretability and relative size of the identified classes (Hagenaars & McCutcheon, 2002; Masyn, 2013; Nylund-Gibson & Choi, 2018).

In order to identify different drug use profiles, models postulating $k+1$ classes ranging from 1 to 10 were sequentially fitted to our data, using each of the 21 binary past 12 month drug use variables as indicators. All models used maximum likelihood estimation and multiple starting values to avoid local maxima and convergence on a local, rather than global, solution. Fit indices Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and sample size adjusted Bayesian Information Criterion (aBIC) were examined with lower values indicating better model fit. The Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) which compares a given model to one with $k-1$ classes was also considered, with a non-significant result lending support to the solution with $k-1$ classes. Entropy was also examined as a measure of the precision of class assignment, with values closer to 1 indicating greater class separation. Finally, class sample size and theoretical interpretability were considered to ascertain that identified classes represented meaningful subgroups of drug users. These analyses were conducted in Mplus version 8.2 (Muthén & Muthén, 2018).

3.2.3.1.1 Approaches to estimating associations between latent class, distal outcomes and covariates

When investigating the associations between latent class and distal outcomes and covariates, one common method is to treat latent class membership as a manifest observed variable in tests such as ANOVAs and regressions, referred to as the classify-analyze approach (Nylund-Gibson, Grimm, & Masyn, 2019). However, in LCA, participants are assigned a probability of belonging to each modelled class and a most likely class variable is defined reflecting which class their probability of membership is the highest. Therefore

treating most likely class as an exact variable does not take into account varying probabilities of membership, such that, for example, in a two class model a participant belonging to class 1 with 0.51 probability would be treated the same as a participant belonging to class 1 with a probability of 1.00 (Clark & Muthén, 2009). This classification error, in turn, may lead to biased estimates in subsequent investigations into associations between latent class membership and traits of interest (Clark & Muthén, 2009).

One way to avoid this potential for bias is to include distal outcomes and covariates in the models estimating the number of latent classes, known as the one step approach (Clark & Muthén, 2009; Nylund-Gibson et al., 2019). A major drawback to this method, however, is that by including outcomes and covariates at this stage, they essentially act as additional indicator variables for latent class formation. As such these variables can have a dramatic influence on latent class formation and lead to very different solutions (Asparouhov & Muthén, 2014a; Feingold, Tiberio, & Capaldi, 2014; Nylund-Gibson & Masyn, 2016), thus it is now recommended to enumerate classes solely using intended indicators prior to estimating associations with other variables (Nylund-Gibson & Masyn, 2016).

Two approaches that account for class classification error are recommended when estimating associations between distal outcomes and covariates: the Bolck, Croon, and Hagonaars (BCH) 3-step (Asparouhov & Muthén, 2014b; Bolck, Croon, & Hagonaars, 2004) and the manual ML 3-step (Vermunt, 2010). Both methods, however, have their own limitations. The BCH method calculates weights that account for measurement error in the latent class variable. These weights can sometimes take on negative values, which can cause variance in the distal outcome also taking negative values leading to inadmissible results (Asparouhov & Muthén, 2014b; Nylund-Gibson et al., 2019). The manual ML 3-step approach has the similar drawback to the one-step approach in that class formation can change from the first step that enumerates classes to the third step that estimates relationships with distal outcomes and covariates. This is because the classification error that is calculated in the second step is the estimated average classification error in the sample as a whole, and the third step assumes this is applied to all participants in a uniform fashion (Nylund-Gibson et al., 2019).

3.2.3.2 Associations between latent classes of polydrug use, socio-demographic characteristics, well-being and hazardous alcohol and drug use

In order to assess the discriminant validity of the chosen latent class solution, chi-square omnibus tests were conducted on gender, country of residence and highest level of education, while omnibus ANOVA tests were conducted on age and number of events attended in the past 12 months.

When attempting to investigate the relationship between latent class membership and well-being and hazardous alcohol and substance use, both the BCH and manual ML 3-step method failed to converge on trustworthy solutions. The BCH method calculated negative weights, while class proportions altered dramatically when performing the third step of the ML 3-step approach. Given the failure of these three step procedures, latent class classification error was accounted for using proportional assignment (Bakk, Tekle, & Vermunt, 2013; Bakk & Vermunt, 2016; Goodman, 2007) when associating class membership with WHO5, AUDIT-C and DUDIT scores. Proportional assignment involves assigning participants to a latent class in proportion to their estimated probability of belonging to that class (Bakk et al., 2013; Bakk & Vermunt, 2016; Goodman, 2007), thus linear regression models with indices of wellbeing and hazardous alcohol and drug use as the outcome were run using class membership probabilities as independent variables. Final estimates were also adjusted for age, gender, country of residence, event attendance and education level. These analyses were conducted in SPSS version 25 (IBM IBM Corp, 2017).

3.3 Results

3.3.1 Sample characteristics

The majority of participants were male (69.05%; see Table 3.1), with a mean age of 23.54 (SD 4.31) and attended on average 18.78 electronic dance music events in the past 12 months. Overall, 83.32% of the sample had achieved a level of education equivalent to GCSEs / A-Levels / key stage 3 or higher. With regard to country of residence, the highest proportion of participants were living in the Netherlands (26.39%), followed by the UK (25.59%), Sweden (17.04%), Belgium (16.72%) and Italy (14.26%). The proportions of the overall sample who endorsed past 12 month use of each drug are shown in Figure 3.1.

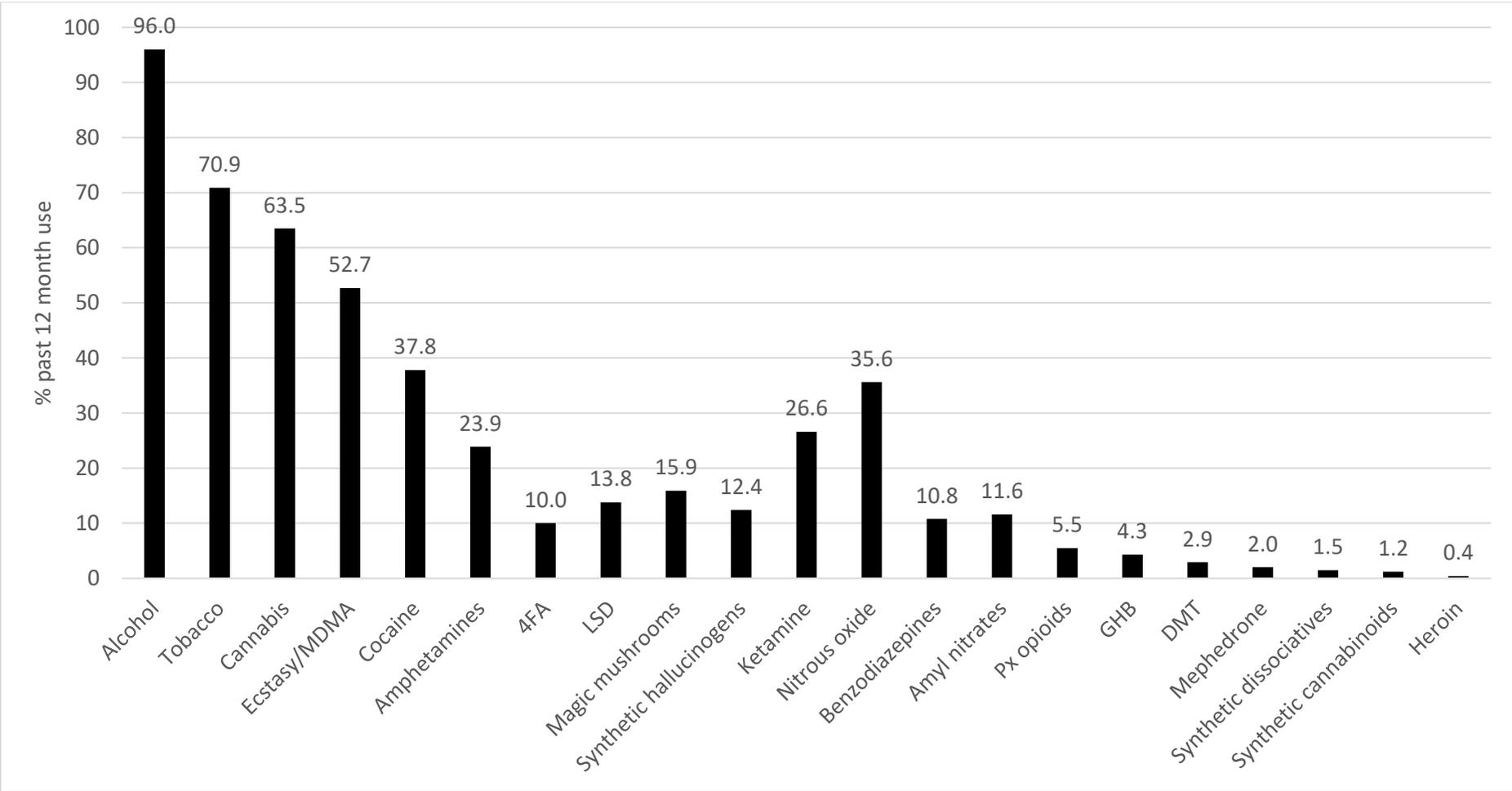
Table 3.1: Socio-demographic characteristics, WHO-5, AUDIT and DUDIT scores by latent class and for the sample as a whole

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use – stimulants	Omnibus test statistic
N (%)	8045 (100%)	1352 (16.81%)	2470 (30.70%)	1291 (16.05%)	1567 (19.48%)	841 (10.45%)	524 (6.51%)	
Age	23.54 (±0.09)	23.17 (±0.15)	23.20 (±0.17)	23.88 (±0.24)	24.09 (±0.21)	23.51 (±0.28)	23.71 (±0.33)	$F_{(5,8039)}=11.89, p<0.001$
Gender								
Male	69.05%	73.00%	70.24%	63.75%	64.58%	72.77%	73.66%	$\chi^2_{(20)}=60.91, p<0.001$
Female	30.29%	26.33%	29.07%	35.71%	34.72%	26.16%	26.34%	
Other	0.66%	0.67%	0.69%	0.54%	0.70%	1.07%	0%	
Country of residence								
Belgium	16.72%	26.04%	23.28%	9.06%	11.93%	10.46%	4.96%	$\chi^2_{(20)}=3201.74, p<0.001$
Italy	14.26%	24.26%	26.36%	2.71%	6.96%	2.85%	0%	
Netherlands	26.39%	15.24%	12.87%	49.57%	18.06%	24.26%	90.08%	
Sweden	17.04%	20.56%	22.39%	14.33%	14.81%	13.56%	1.72%	
UK	25.59%	13.91%	15.10%	24.32%	48.25%	48.87%	3.24%	
Education								
Primary school / key stage 1 and 2	1.57%	2.45%	1.84%	1.12%	1.03%	1.67%	0.80%	$\chi^2_{(20)}=189.53, P<0.001$
Secondary school / key stage 3	13.74%	17.53%	17.19%	11.51%	10.12%	10.72%	9.04%	

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use – stimulants	Omnibus test statistic
GCSE / A-level / key stage 4	52.89%	53.22%	54.10%	51.89%	47.91%	55.51%	59.68%	
University degree / NVQ4 or higher	30.43%	25.78%	24.58%	34.60%	39.66%	31.35%	30.29%	
Missing	1.38%	1.02%	2.29%	0.88%	1.28%	0.75%	0.19%	
Events past 12 months	18.78 (±0.39)	15.61 (±0.90)	18.57 (±0.74)	15.85 (±0.72)	20.99 (±0.92)	24.49 (±1.46)	19.40 (±1.43)	F _(5,8034) =38.40, p<0.001
WHO-5	62.66 (±0.41)	63.41 (±1.01)	60.19 (±0.76)	66.22 (±0.88)	62.37 (±0.86)	62.04 (±1.20)	65.47 (±1.40)	F _(5,8039) =21.68, p<0.001
AUDIT-C – mean	5.41 (±0.05)	3.77 (±0.15)	5.44 (±0.09)	5.41 (±0.13)	6.25 (±0.10)	5.89 (±0.16)	6.10 (±0.18)	F _(5,8039) =201.61, p<0.001
AUDIT-C – >=4	80.96%	56.66%	82.19%	82.96%	91.83%	87.04%	90.65%	χ ² ₍₅₎ =695.94, p<0.001
DUDIT	6.24 (±0.10)	0.49 (±0.13)	3.61 (±0.19)	7.10 (±0.14)	9.45 (±0.26)	13.51 (±0.45)	10.17 (±0.41)	F _(5,8039) =1171.66, p<0.001

NB Proportions are expressed as percentages; mean scores of continuous variables are given with 95% confidence intervals in parentheses.
Abbreviations: UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO-5 – World Health Organisation – Five Well-Being Index; AUDIT – Alcohol Use Disorders Identification Test – Consumption; DUDIT - Drug Use Disorders Identification Test.

Figure 3.1: Past 12 month use of drugs used as LCA indicators



No data were missing for past 12 month drug use, thus all participants were included in the latent class analysis. Five (0.06%) individuals reported attending more than 365 electronic dance music events in the past 12 months thus were recoded as 'missing', while 111 participants (1.4%) did not complete questions regarding education. As such, missing data from these two variables were excluded listwise in regression models, resulting in a final sample of 7,929 for these analyses.

3.3.2 LCA of past 12 month drug use

3.3.2.1 Model enumeration

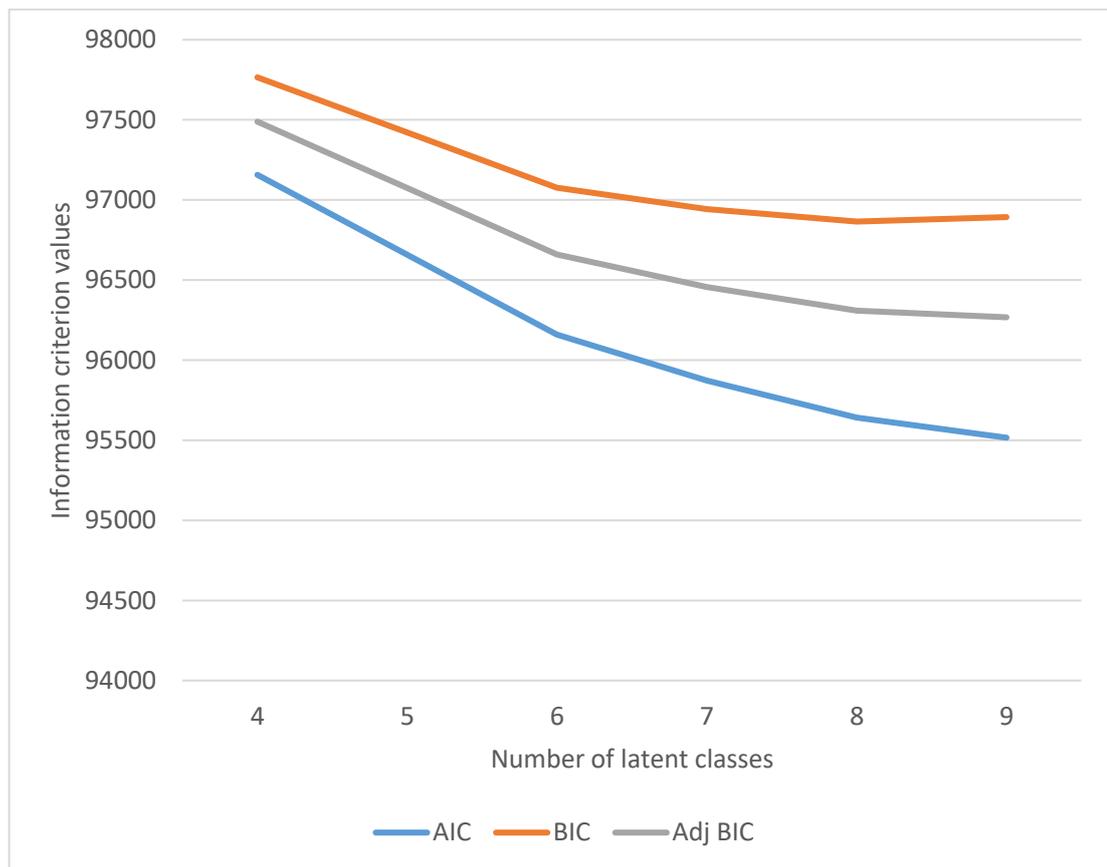
Fit indices (AIC; BIC; aBIC) continued to improve when sequentially fitting 1 to 10 latent class models, indicating failure to reach a global minimum solution (see Table 3.2). As discussed, this is not uncommon when performing latent class analyses with real world data (Masyn, 2013; Nylund-Gibson & Choi, 2018). In cases such as this, model enumeration can be determined by examining each solution in terms of its interpretability and class proportions, while also plotting fit indices to identify an 'elbow' to show at which point the magnitude of decreases reduce (Nylund-Gibson & Choi, 2018). Following examination of all 1 to 10 class models, it was decided that a 6 class solution best fitted our data with regard to class size and theoretical meaning, and that fitting additional classes did not result in distinct past 12 month drug use profiles that represented substantive sub-groups of polydrug users. The 6 class solution was also supported by plotting fit indices (Figure 3.2), which indicated that it was at this point the 'elbow' of reduction magnitude was reached. Furthermore, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) reached non-significance when fitting the 7 class model ($p=0.42$), suggesting that the six class solution better explained the data.

Table 3.2: Past 12 month drug use LCA model fit indices for 1 to 10 classes

Classes	AIC	BIC	Adjusted BIC	Entropy	LMR p-value
1	122137.295	122284.144	122217.41	-	-
2	100747.428	101048.119	100911.473	0.887	<0.001
3	97898.183	98352.716	98146.158	0.821	<0.001
4	97156.741	97765.115	97488.646	0.746	<0.001
5	96658.447	97420.663	97074.282	0.754	0.0028
6	96159.354	97075.412	96659.119	0.739	<0.001
7	95873.082	96942.981	96456.777	0.730	0.42
8	95641.272	96865.013	96308.897	0.723	0.14
9	95515.930	96893.513	96267.485	0.731	0.41
10	95419.523	96950.947	96255.008	0.726	0.27

Selected 6 class solution highlighted in bold

Figure 3.2: AIC, BIC and aBIC fit indices across increasing latent class solutions



3.3.2.2 Description of past 12 month drug use latent classes

The probabilities of endorsement of past 12 month use of each drug in the 6 class model are shown in Figure 3.3, and suggest that classes can be described as follows:

1. *No illicit use* (16.81%): High probability of endorsing alcohol use; low probability of endorsing tobacco use; very low probability of endorsing use of any illicit substance.
2. *Cannabis use* (30.70%): High probability of endorsing alcohol, tobacco and cannabis use; low/very low probabilities of endorsing use of other substances.
3. *Low polydrug use* (16.05%): High probability of endorsing alcohol, tobacco, cannabis and ecstasy/MDMA use; low probability of endorsing cocaine, amphetamine, 4FA, LSD and magic mushroom use.
4. *Moderate polydrug use* (19.48%): High probability of endorsing alcohol, tobacco, cannabis, ecstasy/MDMA and cocaine use; moderate probability of endorsing amphetamine, ketamine and nitrous oxide use.
5. *High polydrug use – hallucinogens/medication* (10.45%): High probability of endorsing alcohol, tobacco, cannabis, ecstasy/MDMA, cocaine, ketamine and nitrous oxide use; moderate possibility of using benzodiazepines, amphetamines, LSD, magic mushrooms, synthetic hallucinogens and prescription opioids.
6. *High polydrug use – stimulants* (6.51%): High probability of endorsing alcohol, tobacco, cannabis, ecstasy/MDMA, cocaine, amphetamines, 4-Fluoroamphetamine (4FA), ketamine and nitrous oxide use; moderate possibility of using synthetic hallucinogens.

3.3.2.3 Latent class demographic characteristics

Table 3.1 displays socio-demographic characteristics by class, along with the results from omnibus test comparisons that show classes significantly differed on all traits. The *Moderate polydrug use* class had the highest mean age, with the lowest mean age observed in the *No illicit use* and *Cannabis use* classes, although the difference between the lowest and highest mean age was less than 1 year (0.9 years). The *No illicit use* and *High polydrug use* classes had the highest proportion of males, with the *Low polydrug use* and *Moderate polydrug use* classes having a higher proportion of females. On average, those in the *High polydrug use – hallucinogens/medication* class attended the most electronic dance music events in the past 12 months, followed by the *Moderate polydrug use* and *High polydrug use – stimulants* classes. Those in the *No illicit use* class attended the fewest events on average in the past 12 months. All polydrug using classes reported higher proportions of having obtained the equivalent of a university degree / NVQ4 or higher than either of the non-polydrug using classes, with the highest observed in the *Moderate polydrug use* class.

Figure 3.3: Probabilities of endorsing past 12 month drug use by latent class for chosen six class solution

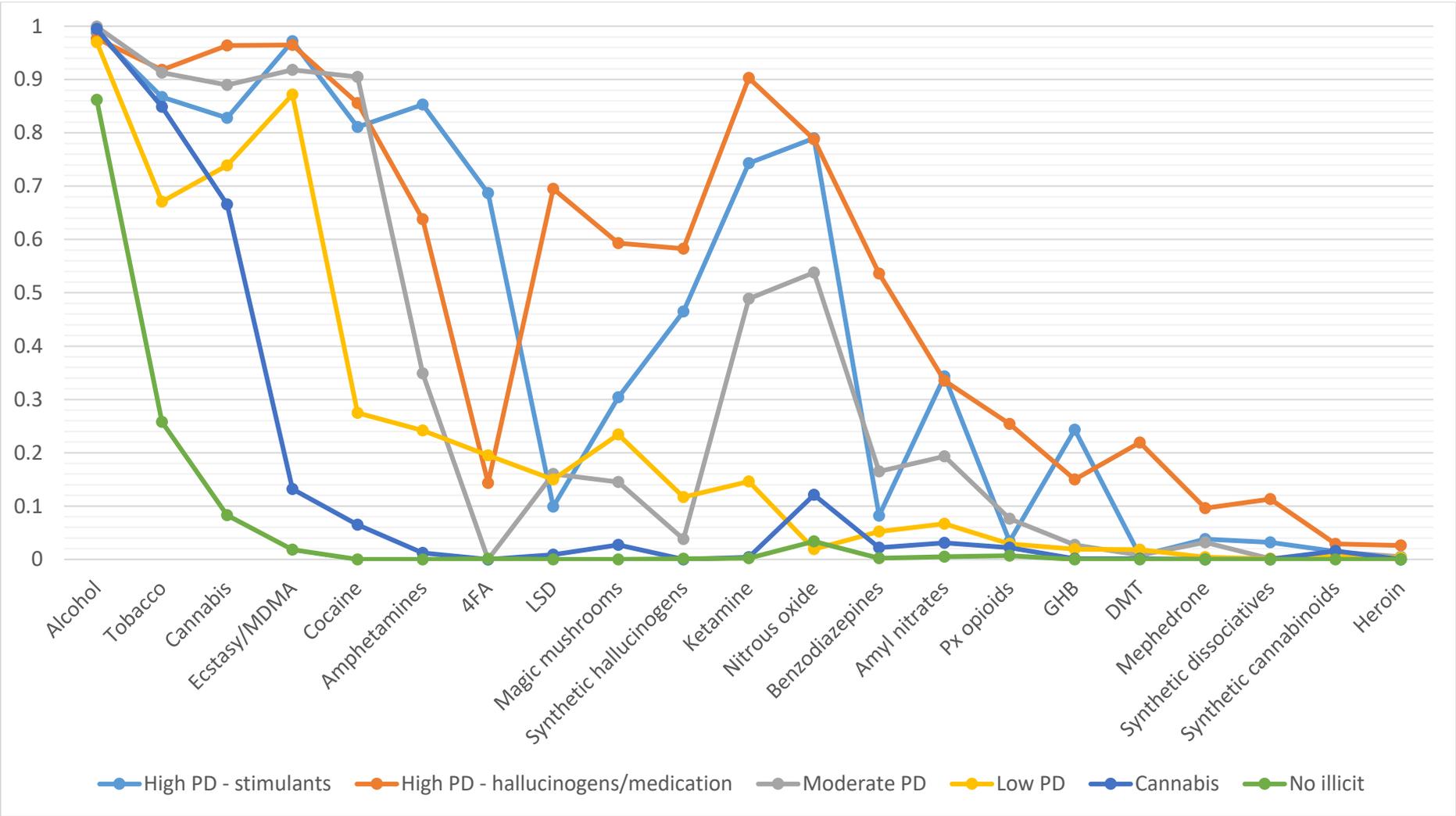


Table 3.3: Drug use frequencies by latent class and for sample as a whole

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Alcohol							
Not in the past 12 months	4.00%	18.42%	0.08%	3.41%	0.06%	2.50%	0.95%
Three times or less in the year	2.11%	3.77%	2.39%	1.55%	0.89%	2.50%	0.95%
Every two or three months	4.14%	6.21%	4.33%	3.80%	2.62%	3.09%	4.96%
Monthly	8.70%	12.20%	9.72%	9.30%	5.36%	7.25%	5.73%
Fortnightly	14.54%	18.57%	16.23%	13.71%	10.66%	14.86%	9.35%
Weekly	45.12%	32.10%	48.02%	49.65%	49.90%	39.83%	48.09%
Three times a week or more	21.38%	8.73%	19.23%	18.59%	30.50%	29.96%	29.96%
Tobacco							
Not in the past 12 months	29.10%	97.12%	11.54%	38.42%	7.08%	7.97%	13.17%
Three times or less in the year	8.69%	0.22%	15.34%	8.60%	7.85%	6.06%	6.11%
Every two or three months	6.14%	0.22%	8.50%	6.51%	7.47%	4.76%	7.63%
Monthly	6.34%	0.22%	7.65%	6.51%	8.30%	7.02%	8.59%
Fortnightly	5.26%	0.07%	5.55%	5.11%	7.47%	8.44%	5.92%
Weekly	8.35%	0.30%	8.18%	7.51%	13.15%	11.53%	12.60%
Three times a week or more	36.12%	1.85%	43.24%	27.34%	48.69%	54.22%	45.99%
Cannabis							
Not in the past 12 months	36.52%	98.00%	39.72%	26.57%	10.59%	3.45%	17.94%
Three times or less in the year	16.93%	0.52%	21.74%	22.77%	21.31%	11.18%	18.32%
Every two or three months	11.03%	0.30%	11.90%	12.24%	15.95%	11.41%	16.22%
Monthly	8.33%	0.30%	7.37%	9.68%	12.64%	12.25%	11.07%
Fortnightly	6.18%	0.00%	5.10%	6.51%	9.13%	12.25%	7.82%
Weekly	8.03%	0.07%	6.40%	9.37%	11.55%	14.39%	12.21%
Three times a week or more	12.99%	0.81%	7.77%	12.86%	18.83%	35.08%	16.41%
Ecstasy/MDMA							
Not in the past 12 months	47.30%	96.67%	90.20%	9.14%	7.15%	2.97%	2.86%
Three times or less in the year	17.25%	1.55%	5.79%	36.33%	30.12%	24.61%	14.50%

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Every two or three months	18.52%	1.41%	2.67%	34.70%	31.84%	31.63%	36.64%
Monthly	12.33%	0.37%	0.93%	16.27%	22.02%	26.16%	36.07%
Fortnightly	3.54%	0.00%	0.32%	2.71%	6.57%	11.06%	8.78%
Weekly	0.97%	0.00%	0.08%	0.77%	2.17%	3.09%	1.15%
Three times a week or more	0.09%	0.00%	0.00%	0.08%	0.13%	0.48%	0.00%
Cocaine							
Not in the past 12 months	62.20%	100.00%	94.78%	81.25%	3.64%	13.56%	17.37%
Three times or less in the year	17.85%	0.00%	3.40%	11.62%	44.48%	35.32%	39.69%
Every two or three months	8.75%	0.00%	0.93%	3.87%	23.87%	17.60%	20.80%
Monthly	6.24%	0.00%	0.61%	1.94%	16.15%	17.12%	12.40%
Fortnightly	2.98%	0.00%	0.16%	0.77%	7.28%	9.04%	6.87%
Weekly	1.62%	0.00%	0.12%	0.46%	3.96%	5.23%	2.86%
Three times a week or more	0.36%	0.00%	0.00%	0.08%	0.64%	2.14%	0.00%
Amphetamines							
Not in the past 12 months	76.08%	100.00%	100.00%	75.37%	63.88%	34.24%	11.45%
Three times or less in the year	11.72%	0.00%	0.00%	15.03%	21.19%	28.06%	31.68%
Every two or three months	5.26%	0.00%	0.00%	4.57%	6.76%	13.20%	27.48%
Monthly	3.46%	0.00%	0.00%	2.40%	4.08%	10.34%	18.32%
Fortnightly	1.93%	0.00%	0.00%	1.24%	2.30%	7.73%	7.06%
Weekly	0.99%	0.00%	0.00%	0.77%	1.08%	4.16%	3.24%
Three times a week or more	0.56%	0.00%	0.00%	0.62%	0.70%	2.26%	0.76%
4FA							
Not in the past 12 months	89.96%	100.00%	100.00%	78.85%	100.00%	86.80%	19.47%
Three times or less in the year	5.85%	0.00%	0.00%	13.56%	0.00%	8.68%	42.18%
Every two or three months	2.51%	0.00%	0.00%	5.11%	0.00%	2.14%	22.52%
Monthly	1.35%	0.00%	0.00%	2.25%	0.00%	1.43%	12.98%
Fortnightly	0.24%	0.00%	0.00%	0.15%	0.00%	0.71%	2.10%
Weekly	0.07%	0.00%	0.00%	0.08%	0.00%	0.24%	0.57%
Three times a week or more	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.19%
LSD							

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Not in the past 12 months	86.18%	100.00%	99.51%	83.97%	85.26%	26.04%	92.37%
Three times or less in the year	10.17%	0.00%	0.40%	12.63%	12.51%	49.46%	6.30%
Every two or three months	2.46%	0.00%	0.04%	2.17%	1.47%	16.65%	1.15%
Monthly	0.81%	0.00%	0.04%	0.93%	0.64%	4.88%	0.19%
Fortnightly	0.27%	0.00%	0.00%	0.23%	0.06%	2.14%	0.00%
Weekly	0.07%	0.00%	0.00%	0.00%	0.06%	0.59%	0.00%
Three times a week or more	0.04%	0.00%	0.00%	0.08%	0.00%	0.24%	0.00%
Magic Mushrooms							
Not in the past 12 months	84.11%	100.00%	97.81%	74.52%	86.41%	37.46%	70.23%
Three times or less in the year	13.47%	0.00%	2.15%	22.77%	11.93%	48.87%	26.53%
Every two or three months	1.93%	0.00%	0.04%	2.40%	1.53%	9.87%	3.05%
Monthly	0.36%	0.00%	0.00%	0.23%	0.13%	2.73%	0.19%
Fortnightly	0.07%	0.00%	0.00%	0.00%	0.00%	0.71%	0.00%
Weekly	0.04%	0.00%	0.00%	0.08%	0.00%	0.24%	0.00%
Three times a week or more	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Synthetic hallucinogens							
Not in the past 12 months	87.61%	100.00%	100.00%	86.37%	97.64%	38.76%	48.85%
Three times or less in the year	8.74%	0.00%	0.00%	10.46%	2.11%	38.29%	40.46%
Every two or three months	2.55%	0.00%	0.00%	2.17%	0.26%	14.98%	8.97%
Monthly	0.80%	0.00%	0.00%	0.85%	0.00%	5.47%	1.34%
Fortnightly	0.26%	0.00%	0.00%	0.08%	0.00%	2.26%	0.19%
Weekly	0.04%	0.00%	0.00%	0.08%	0.00%	0.12%	0.19%
Three times a week or more	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Ketamine							
Not in the past 12 months	73.41%	99.78%	99.68%	86.21%	50.80%	7.37%	23.66%
Three times or less in the year	12.08%	0.07%	0.28%	9.30%	27.57%	29.96%	30.53%
Every two or three months	6.70%	0.00%	0.04%	2.40%	11.61%	23.19%	24.81%
Monthly	4.13%	0.07%	0.00%	1.32%	5.87%	18.31%	12.98%
Fortnightly	2.05%	0.00%	0.00%	0.46%	2.36%	10.94%	5.73%
Weekly	1.29%	0.07%	0.00%	0.23%	1.40%	7.85%	2.29%

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Three times a week or more	0.34%	0.00%	0.00%	0.08%	0.38%	2.38%	0.00%
Nitrous oxide							
Not in the past 12 months	64.45%	96.60%	90.28%	49.96%	46.01%	21.05%	20.23%
Three times or less in the year	17.61%	2.59%	6.40%	30.60%	25.85%	28.30%	35.50%
Every two or three months	9.47%	0.52%	1.90%	11.46%	15.12%	23.19%	24.43%
Monthly	5.30%	0.07%	0.97%	5.34%	7.91%	15.46%	14.89%
Fortnightly	2.04%	0.22%	0.28%	1.78%	3.19%	7.37%	3.63%
Weekly	0.91%	0.00%	0.08%	0.70%	1.40%	3.92%	1.34%
Three times a week or more	0.22%	0.00%	0.08%	0.15%	0.51%	0.71%	0.00%
Benzodiazepines							
Not in the past 12 months	89.25%	99.70%	98.34%	94.50%	83.41%	45.66%	93.89%
Three times or less in the year	5.10%	0.22%	0.57%	3.02%	8.93%	23.42%	3.24%
Every two or three months	2.19%	0.00%	0.24%	1.01%	3.00%	12.37%	1.15%
Monthly	1.55%	0.00%	0.20%	0.54%	2.43%	8.32%	0.95%
Fortnightly	0.70%	0.00%	0.08%	0.15%	0.77%	4.40%	0.57%
Weekly	0.66%	0.07%	0.32%	0.31%	0.57%	3.57%	0.19%
Three times a week or more	0.56%	0.00%	0.24%	0.46%	0.89%	2.26%	0.00%
Amyl nitrates							
Not in the past 12 months	88.35%	99.33%	97.29%	93.34%	80.54%	65.99%	64.89%
Three times or less in the year	7.73%	0.30%	1.94%	4.57%	12.76%	21.88%	24.24%
Every two or three months	1.86%	0.15%	0.32%	1.32%	3.38%	5.11%	5.15%
Monthly	1.18%	0.15%	0.24%	0.39%	1.79%	4.04%	3.82%
Fortnightly	0.50%	0.07%	0.08%	0.31%	0.77%	1.66%	1.34%
Weekly	0.27%	0.00%	0.08%	0.08%	0.51%	0.95%	0.57%
Three times a week or more	0.10%	0.00%	0.04%	0.00%	0.26%	0.36%	0.00%
Prescription opioids							
Not in the past 12 months	94.48%	99.19%	98.02%	97.29%	92.72%	73.84%	97.14%
Three times or less in the year	2.91%	0.15%	0.81%	1.01%	4.28%	14.98%	1.15%
Every two or three months	0.94%	0.07%	0.36%	0.46%	1.02%	5.23%	0.00%
Monthly	0.51%	0.00%	0.12%	0.39%	0.57%	2.62%	0.38%

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Fortnightly	0.21%	0.00%	0.04%	0.15%	0.26%	0.95%	0.38%
Weekly	0.24%	0.07%	0.16%	0.00%	0.26%	1.19%	0.00%
Three times a week or more	0.71%	0.52%	0.49%	0.70%	0.89%	1.19%	0.95%
GHB							
Not in the past 12 months	95.75%	100.00%	99.92%	98.22%	97.32%	84.42%	72.52%
Three times or less in the year	2.50%	0.00%	0.08%	1.32%	1.85%	8.44%	15.65%
Every two or three months	0.68%	0.00%	0.00%	0.23%	0.57%	2.50%	4.20%
Monthly	0.50%	0.00%	0.00%	0.08%	0.26%	1.78%	3.82%
Fortnightly	0.37%	0.00%	0.00%	0.08%	0.00%	1.78%	2.67%
Weekly	0.15%	0.00%	0.00%	0.00%	0.00%	0.71%	1.15%
Three times a week or more	0.05%	0.00%	0.00%	0.08%	0.00%	0.36%	0.00%
DMT							
Not in the past 12 months	97.13%	100.00%	99.96%	97.99%	99.36%	77.05%	99.81%
Three times or less in the year	2.34%	0.00%	0.04%	1.70%	0.57%	18.43%	0.19%
Every two or three months	0.35%	0.00%	0.00%	0.15%	0.00%	3.09%	0.00%
Monthly	0.09%	0.00%	0.00%	0.08%	0.00%	0.71%	0.00%
Fortnightly	0.04%	0.00%	0.00%	0.08%	0.00%	0.24%	0.00%
Weekly	0.04%	0.00%	0.00%	0.00%	0.06%	0.24%	0.00%
Three times a week or more	0.02%	0.00%	0.00%	0.00%	0.00%	0.24%	0.00%
Mephedrone							
Not in the past 12 months	98.05%	100.00%	100.00%	99.69%	96.75%	90.01%	96.56%
Three times or less in the year	1.24%	0.00%	0.00%	0.23%	2.11%	6.54%	1.72%
Every two or three months	0.30%	0.00%	0.00%	0.08%	0.51%	1.07%	1.15%
Monthly	0.17%	0.00%	0.00%	0.00%	0.13%	1.19%	0.38%
Fortnightly	0.14%	0.00%	0.00%	0.00%	0.32%	0.59%	0.19%
Weekly	0.05%	0.00%	0.00%	0.00%	0.13%	0.24%	0.00%
Three times a week or more	0.05%	0.00%	0.00%	0.00%	0.06%	0.36%	0.00%
Synthetic dissociatives							
Not in the past 12 months	98.51%	100.00%	100.00%	99.85%	99.94%	88.11%	96.76%
Three times or less in the year	0.91%	0.00%	0.00%	0.08%	0.06%	7.13%	2.10%

	Whole sample	No illicit use	Cannabis use	Low polydrug use	Moderate polydrug use	High polydrug use – hall./meds.	High polydrug use - stimulants
Every two or three months	0.30%	0.00%	0.00%	0.08%	0.00%	2.26%	0.76%
Monthly	0.21%	0.00%	0.00%	0.00%	0.00%	1.90%	0.19%
Fortnightly	0.05%	0.00%	0.00%	0.00%	0.00%	0.36%	0.19%
Weekly	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Three times a week or more	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Synthetic cannabinoids							
Not in the past 12 months	98.82%	100.00%	98.66%	99.38%	98.66%	97.15%	98.28%
Three times or less in the year	0.65%	0.00%	0.77%	0.31%	0.77%	1.55%	0.76%
Every two or three months	0.19%	0.00%	0.16%	0.15%	0.19%	0.48%	0.38%
Monthly	0.19%	0.00%	0.24%	0.08%	0.13%	0.59%	0.19%
Fortnightly	0.07%	0.00%	0.08%	0.00%	0.06%	0.12%	0.38%
Weekly	0.05%	0.00%	0.08%	0.00%	0.13%	0.00%	0.00%
Three times a week or more	0.04%	0.00%	0.00%	0.08%	0.06%	0.12%	0.00%
Heroin							
Not in the past 12 months	99.58%	100.00%	100.00%	99.69%	99.49%	97.38%	100.00%
Three times or less in the year	0.20%	0.00%	0.00%	0.15%	0.26%	1.19%	0.00%
Every two or three months	0.07%	0.00%	0.00%	0.08%	0.06%	0.48%	0.00%
Monthly	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Fortnightly	0.01%	0.00%	0.00%	0.00%	0.06%	0.00%	0.00%
Weekly	0.01%	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%
Three times a week or more	0.11%	0.00%	0.00%	0.08%	0.13%	0.71%	0.00%

Differences between classes with regard to country of residence were also observed. Participants resident in Italy, and to a lesser extent Belgium and Sweden, were predominantly members of *No illicit use* or *Cannabis use* classes. Conversely, the majority of members of all four polydrug using classes were resident in either the UK or the Netherlands. Both *Moderate polydrug use* and *High polydrug use – hallucinogens/medication* classes had the highest proportion of participants living in the UK, while the *Low polydrug use* and *High polydrug use – stimulants* classes contained the highest proportions of those living in the Netherlands. This relationship between country of residence and class membership can be seen in Figure 3.4, which shows the proportions of class membership within each country.

The frequencies of use of each drug are displayed in Table 3.3, which shows that as well as the use of more drugs in the past 12 months, the both *High polydrug use* classes tended to have used more frequently. However, the majority of drugs were used monthly or less often, even amongst the classes exhibiting the most frequent use.

Figure 3.4: Proportions of latent classes within UK, Netherlands, Belgium, Sweden and Italy

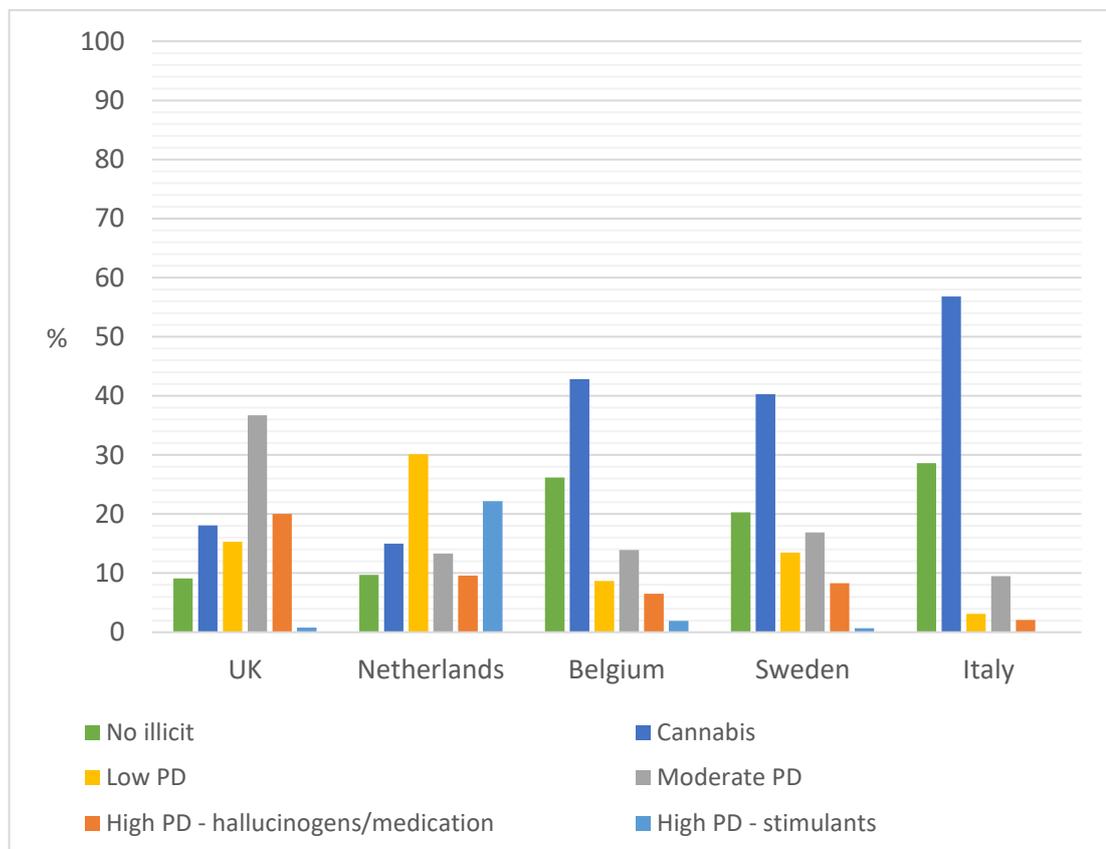


Table 3.4: Results from WHO-5, AUDIT-C and DUDIT linear regression models adjusted for gender, country of residence, education and event attendance

	WHO-5			AUDIT-C			DUDIT		
	B (95% CI)	Beta	p	B (95% CI)	Beta	p	B (95% CI)	Beta	p
Latent Class									
No illicit use	<i>Reference</i>								
Cannabis use	-4.75 (-6.35, -3.15)	-0.086	<0.001	2.29 (2.11, 2.48)	0.32	<0.001	5.34 (4.98, 5.77)	0.29	<0.001
Low PD	3.35 (1.64, 5.07)	0.051	<0.001	1.07 (0.87, 1.27)	0.12	<0.001	8.17 (7.75, 8.59)	0.37	<0.001
Moderate PD	-2.42 (-4.06, -0.79)	-0.040	0.004	2.58 (2.39, 2.77)	0.33	<0.001	10.73 (10.33, 11.13)	0.52	<0.001
High PD – hallucinogens/meds.	-2.53 (-4.35, -0.70)	-0.036	0.007	1.61 (1.40, 1.82)	0.18	<0.001	15.39 (14.94, 15.84)	0.66	<0.001
High PD – stimulants	-0.56 (-2.88, 1.77)	-0.006	0.64	1.75 (1.48, 2.02)	0.15	<0.001	11.20 (10.63, 11.77)	0.38	<0.001
Gender									
Female	<i>Reference</i>								
Male	3.57 (2.69, 4.46)	0.089	<0.001	0.80 (0.69, 0.90)	0.15	<0.001	0.35 (0.13, 0.57)	0.026	0.002
Other	-4.01 (-8.98, 0.97)	-0.018	0.11	-0.72 (-1.29, -0.14)	-0.024	0.02	1.28 (0.055, 2.50)	0.017	0.041
Country of residence									
Belgium	1.86 (0.52, 3.21)	0.038	0.007	0.20 (0.039, 0.35)	0.030	0.014	1.00 (0.67, 1.33)	0.060	<0.001
Italy	-1.77 (-3.25, -0.29)	-0.033	0.02	-1.80 (-1.97, -1.63)	-0.26	<0.001	1.15 (0.78, 1.51)	0.064	<0.001
Netherlands	3.16 (1.88, 4.44)	0.075	<0.001	0.14 (-0.009, 0.29)	0.026	0.066	-0.21 (-0.53, 0.11)	-0.015	0.19
Sweden	0.30 (-1.22, 1.82)	0.006	0.39	-0.41 (-0.58, -0.23)	-0.063	<0.001	-0.051 (-0.42, 0.32)	-0.003	0.79
Italy	-1.77 (-3.25, -0.29)	-0.033	0.02	-1.80 (-1.97, -1.63)	-0.26	<0.001	1.15 (0.78, 1.51)	0.064	<0.001
UK	<i>Reference</i>								
Education									
Primary school / key stage 1 and 2	-3.36 (-6.84, 0.12)	-0.023	0.06	-0.77 (-1.18, -0.37)	-0.040	<0.001	2.11 (1.25, 2.96)	0.042	<0.001

	WHO-5			AUDIT-C			DUDIT		
	B (95% CI)	Beta	p	B (95% CI)	Beta	p	B (95% CI)	Beta	p
Secondary school / key stage 3	-1.24 (-2.82, 0.35)	-0.023	0.13	-0.27 (-0.45, -0.086)	-0.039	0.004	1.37 (0.98, 1.76)	0.076	<0.001
GCSE / A-level / key stage 4	-2.16 (-3.21, -1.10)	-0.058	<0.001	0.068 (-0.054, 0.19)	0.014	0.27	0.78 (0.52, 1.03)	0.062	<0.001
University degree / NVQ4 or higher	<i>Reference</i>								
Age	0.054 (-0.06, 0.17)	0.013	0.95	-0.047 (-0.060, -0.034)	-0.084	<0.001	0.012 (-0.015, 0.040)	0.008	0.87
Events past 12 months	0.049 (0.03, 0.07)	0.047	<0.001	0.015 (0.012, 0.018)	0.11	<0.001	0.007 (0.002, 0.013)	0.021	0.011

B – unstandardized regression coefficient; Beta – standardized regression coefficient; 95% CI – 95% confidence interval. Abbreviations: PD – polydrug use; UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO-5 – World Health Organisation – Five Well-Being Index; AUDIT – Alcohol Use Disorders Identification Test – Consumption; DUDIT - Drug Use Disorders Identification Test.

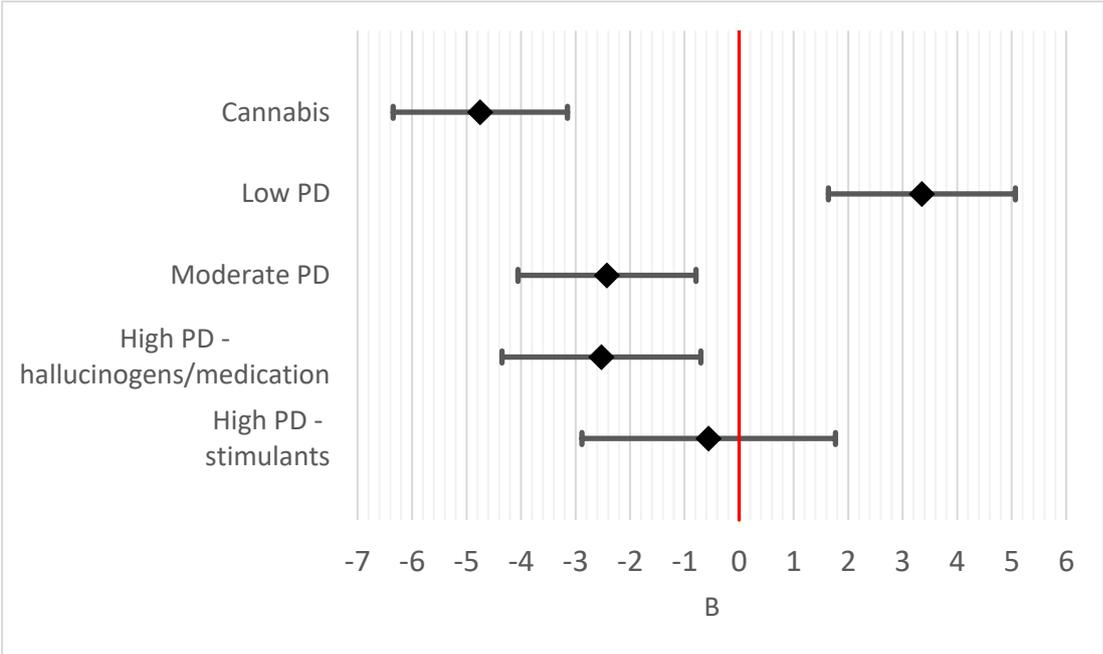
3.3.2.4 Associations between latent class and well-being, and problematic alcohol and drug use

Table 3.4 reports the results of linear regression models with WHO-5, AUDIT-C and DUDIT scores regressed on latent class membership probabilities and socio-demographic covariates. Regression coefficients indicate that WHO-5, AUDIT-C and DUDIT scores differed significantly across latent classes when adjusting for gender, country of residence, highest education level, age and number of electronic dance music events attended in the past 12 months.

3.3.2.4.1 WHO-5

Figure 3.5 shows that in comparison to the *No illicit use* class, the *Cannabis use*, *Moderate polydrug use* and *High polydrug use – hallucinogens/medication* classes were associated with lower WHO-5 scores, while higher scores were observed in the *Low polydrug use* class. No differences were observed between the *No illicit use* class and *High polydrug use – stimulants* class. Membership of the *Cannabis use* class was associated with the lowest WHO-5 scores, while the *Low polydrug use* class was associated with the highest.

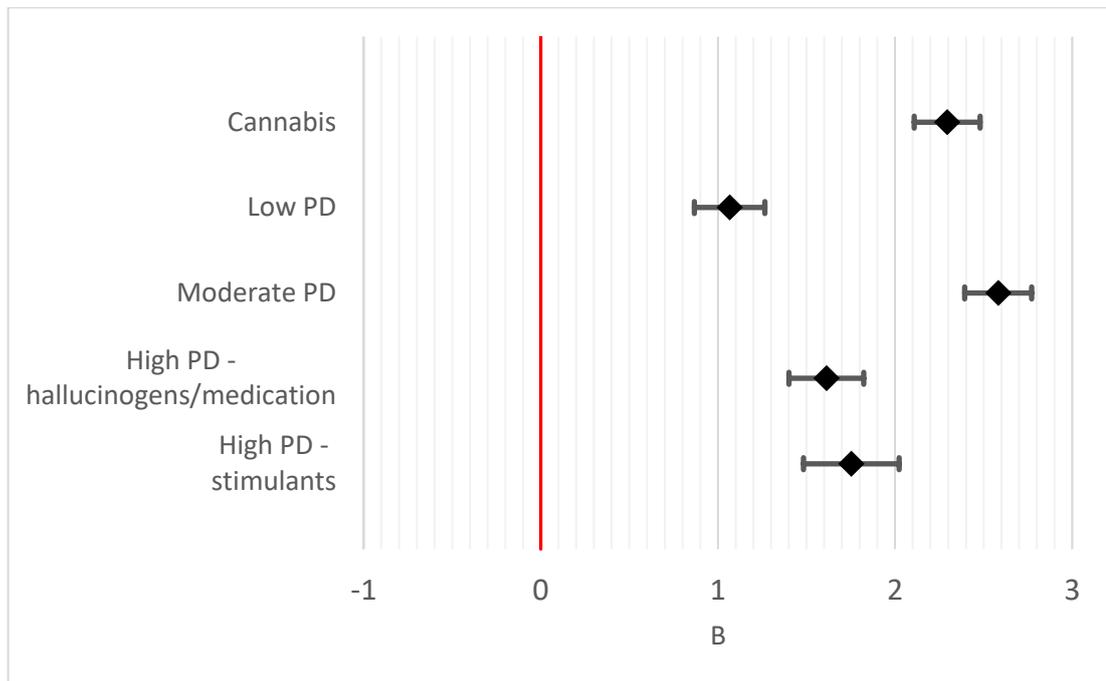
Figure 3.5: Regression coefficients and 95% confidence intervals for associations between latent class (compared to No illicit use) and WHO-5 scores, adjusted for gender, country of residence, education and event attendance



3.3.2.4.2 AUDIT-C

As shown in Figure 3.6, all latent classes were associated with significantly higher AUDIT-C scores when compared to the *No illicit use* class. The *Moderate polydrug use* class was associated with the highest AUDIT-C scores.

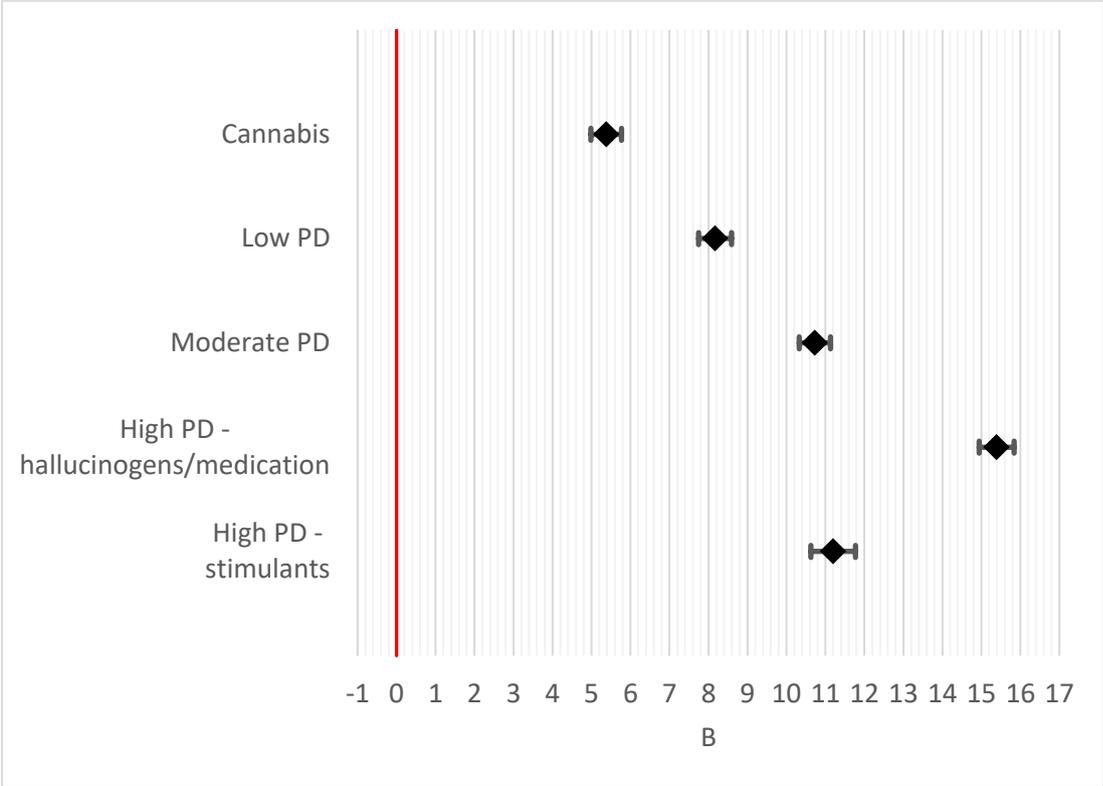
Figure 3.6: Regression coefficients and 95% confidence intervals for associations between latent class (compared to *No illicit use*) and AUDIT-C scores, adjusted for gender, country of residence, education and event attendance



3.3.2.4.3 DUDIT

Figure 3.7 indicates that, in comparison to the *No illicit use* class, membership of all other classes was associated with increased DUDIT scores. The *High polydrug use – hallucinogens/medication* was associated with the highest DUDIT score. Figure 3.7 also shows that DUDIT scores increased in a ‘dose-response’ pattern as levels of polydrug use increased: both *High polydrug use* classes were associated with higher DUDIT scores than the *Moderate polydrug use* class, which in turn was associated with higher scores than the *Low polydrug use* class, with the *Cannabis use* class associated with the lowest score of the five.

Figure 3.7: Regression coefficients and 95% confidence intervals for associations between latent class (compared to No illicit use) and DUDIT scores, adjusted for gender, country of residence, education and event attendance



3.4 Discussion

Latent class analysis identified six discrete classes of polydrug use amongst a sample of over 8,000 young adults engaging with the European nightlife scene living in Belgium, Italy, Netherlands, Sweden and the UK, based upon their past 12 month use of 21 different licit and illicit drugs. The identified classes were characterized as follows: *No illicit use* (16.81%); *Cannabis use* (30.70%); *Low polydrug use* (16.05%); *Moderate polydrug use* (19.48%); *High polydrug use – hallucinogens/medication* (10.45%); *High polydrug use – stimulants* (6.51%). The extent to which the lines on the probability plot (Figure 3.3) intersect indicates that LCA identified polydrug profiles that reflect distinct patterns of use beyond simply an increase in the number of drugs used in the past 12 months. These findings suggest there is considerable heterogeneity in drug use patterns in the European nightlife populations, and are in line with previous LCA studies that show polydrug use patterns to be more nuanced than simply additive (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017).

3.4.1 Latent polydrug use classes

Almost half (47.51%) of the sample was characterized by the use of one illicit drug (cannabis) or fewer in the past 12 months, supporting findings of substantial proportions of non-polydrug users in other LCA studies amongst nightlife populations (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017; Sanudo et al., 2015) and completers of the GDS (Morley et al., 2015). The remaining 52.49% of the sample were classified into one of four polydrug classes, with patterns of use differing considerably.

Two classes of high polydrug use were identified, characterized by either high probabilities of endorsing past 12 month hallucinogen/medication or wider stimulant use. This is in line with Fernández-Calderón and colleagues' (2018) finding of two moderate polydrug using classes differentiated by use of stimulants or psychedelics, and with Hannemann et al's (2017) identification of a distinct "Psychedelic class". These two studies were also conducted amongst those engaging specifically with the electronic dance music scene, and taken together lend weight to suggestions that psychedelics/hallucinogens may be a particular feature of electronic dance music culture (F. Fernández-Calderón et al., 2018; F. Fernández-Calderón et al., 2011).

In the current study, one High polydrug using group was characterized by higher probabilities of amphetamine and 4FA use (*High polydrug use – stimulants*), while the other by higher probabilities of endorsing past 12 month use of LSD, magic mushrooms and synthetic hallucinogens (*High polydrug use – hallucinogens/medication*). While this pattern is reflective of differences between Fernández-Calderón et al's (2018) two Moderate using groups, the authors observed increased probability of benzodiazepine use amongst the stimulant compared to the psychedelic class. This is the opposite relationship to that observed in this study, with the *High polydrug use – hallucinogen/medication* class having the highest overall probability of benzodiazepine use (0.54), compared to 0.08 amongst the *High polydrug use – stimulants* class. Although a more moderate difference, an elevated probability of prescription opioid use was also observed in the hallucinogen class (0.25) over all other classes, with a very low probability observed in the stimulant class (0.03). The use of depressants such as benzodiazepines to counteract the effect of stimulants is cited as a possible explanation for higher observed probabilities amongst stimulant using groups by Fernández-Calderón (F. Fernández-Calderón et al., 2018; Hunt et al., 2009). Members of the *High polydrug – hallucinogen/medication* class had a high probability of using cocaine (0.86), and so this practice cannot be ruled out. However, it does not explain why similar

rates of benzodiazepine use were not observed amongst the *High polydrug use – stimulants* class. The potential link between hallucinogen and medication use therefore warrants further investigation.

Differences between the *Low* and *Moderate polydrug use* classes were also not defined just in terms of using an additional number of drugs. Both groups had similar probabilities of ecstasy/MDMA use, and the *Low polydrug use* group in fact had higher probabilities of endorsing past 12 month 4FA, magic mushroom and synthetic hallucinogen use. However, these differences were less pronounced than for a number of drugs that the *Moderate* class were more likely to endorse use of, such as cocaine, ketamine and nitrous oxide.

Despite these differences, one still might broadly conceptualise the polydrug use profile model as additive as a spectrum from lower to higher levels of use was certainly identified. Indeed, the most notable differences were found between the two classes characterised by high levels of polydrug use, suggesting that heterogeneity in drug use may be most pronounced at the higher end of this spectrum. As such, it might be that polydrug use among European young adults regularly engaging with the nightlife scene may follow an additive structure with different forms of high levels of polydrug use. Given the preliminary nature of these findings, further LCA studies on European nightlife populations are required to clarify the structure of polydrug use groups in this population.

The class containing the largest proportion of the sample was the *Cannabis use* class (30.7%), echoing results from a study in the nightlife scene in Munich (Hannemann et al., 2017), which identified a cannabis using only class containing approximately a third of their sample (34.9%). Furthermore, all polydrug using classes had a high probability of endorsing cannabis use, similar to findings by Hannemann (2017). This suggests that cannabis use is highly prevalent amongst young adults engaging with the European nightlife scene, consistent with evidence that cannabis remains the most widely used illicit drug in Europe (EMCDDA, 2019).

Beyond cannabis use, there were further similarities between the classes. For example, all identified classes, including the *No illicit use* class, had very high (>0.85) probabilities of endorsing past 12 month alcohol use. Only one LCA study in nightlife populations examined alcohol use (Sanudo et al., 2015), and also found high probabilities of use, defined by episodes of binge drinking. Similarly there are substances with very low endorsement probabilities, such as synthetic cannabinoids and heroin (>0.03 for both drugs across all

classes). Furthermore, polydrug using classes had moderate to high (0.67 – 0.92) probabilities of past 12 month tobacco use.

Elucidating differences between different polydrug use profiles can help inform appropriate strategies around minimizing harm. For example, that almost half the sample was not characterized by polydrug use suggests that not all individuals engaging with the nightlife scene would benefit from efforts directed at education around the dangers of combining different drugs. On the other hand, the high probabilities of cannabis and alcohol across different classes indicate that interventions and harm reduction efforts focused on the potential risks associated with using these substances may be worthwhile. Additionally, given the high probabilities of tobacco use, members of polydrug using classes may benefit from smoking cessation advice. The two High polydrug use groups that were identified highlight profiles of users who are potentially at greater risk of harm than others, given their use of multiple substances, possibly in different combinations, although these cannot be ascertained from the EMSS.

3.4.2 Demographic characteristics

Beyond establishing qualitative differences between the identified classes, the discriminant validity of the chosen solution was confirmed by significant omnibus tests on demographic variables, thus validating this method for identifying distinct polydrug use profiles among populations regularly engaging with the nightlife scene.

While the difference in age across classes was statistically significant, the difference between the youngest on average class (*No illicit use* and *Cannabis use*; 23.2 years) and the oldest on average (*Moderate polydrug use*; 24.1 years) was only 0.9 years. Sanudo et al (Sanudo et al., 2015) found an association between class membership and age only in that those in age groups below 34 were associated with membership of the moderate compared to no use group. Participants in the current study were all aged under 34, and it may be that age does not influence polydrug use amongst young adults to the same extent. This may partly explain why no association was found between age and class membership by Ramo (2010) or Fernández-Calderón (2018), who used broadly similar age ranges to the current study (18-29 and 18-40 respectively), or by Hannemann whose sample had a relatively young mean age (23.1 years).

The gender distributions of the four polydrug use classes support previous findings that being male is associated with membership of classes with more extensive polydrug use

(Hannemann et al., 2017; Sanudo et al., 2015), as both High polydrug using classes contained a higher proportion of males than either the *Low* or *Moderate polydrug use* groups. Interestingly, however, a higher proportion of females was observed in the *Low* and *Moderate polydrug use* classes than in either the *No illicit use* and *Cannabis use* classes, suggesting that the relationship between gender and profiles of drug use in the nightlife populations may be more complex. Indeed, although non-significant, Fernández-Calderón et al (2018) observed the highest proportions of females in both the Non polysubstance using and Moderate polydrug use – stimulant classes. This relationship warrants further exploration, and again highlights the utility of identifying more nuanced patterns of polydrug use.

Country of residence also significantly differed across all classes. The majority of participants living in Belgium, Sweden and Italy were classified as belonging to either the *No illicit use* or *Cannabis use* class, with very few participants from Italy in particular, being members of either polydrug use class. In turn, the four polydrug using classes were largely made up of participants living in the UK and the Netherlands.

Previous LCA studies amongst nightlife populations have all been conducted in one country, thus are unable to investigate country level differences in polydrug use patterns. Morley et al (2015) utilised data from GDS participants living in the UK, Australia or United States, and despite selecting these countries in part due to the fact that levels of drug use were considered similar between them, the proportions of participants from each country varied by class. For example, both the “Non-polysubstance” use and “Cannabis and medication” classes contained the highest proportion of individuals living in the UK (Morley et al., 2015). Although proportions of participants living in the UK in our sample were amongst the lowest in the non-polydrug using classes, approximately half of the class characterized by their use of benzodiazepines and prescription opioids (*High polydrug – hallucinogens/medication*; 48.87%) lived in the UK. Although this group was further characterized by heavy polydrug and hallucinogen use, rather than additionally by cannabis use, taken together with the results of Morley et al. (2015), these findings might suggest that use of medications such as benzodiazepines and prescription opioids is a particular feature of the repertoire of use of a number of young adults regularly engaging with nightlife in the UK.

Country level differences might also reflect the market availability of certain drugs. A relatively large number of drugs were included as latent class indicator variables (21), and it

seems reasonable to suggest that not all of these will be universally available across countries. Indeed, as mentioned, cannabis is the most widely used illicit drug in Europe (EMCDDA, 2019), thus it is not surprising that high probabilities of past 12 month use were observed in all polydrug using classes. Conversely, the differing availability of drugs in certain countries may partly explain some of the country level differences in class membership we observed. The *High polydrug use – stimulants* class was to a certain extent characterized by high probability of the use of 4FA relative to other classes (0.69), with 90.1% of this class living in the Netherlands. Indeed, it is thought that 4FA is particularly associated with use in the Netherlands over and above other European countries (Hondebrink et al., 2015; Linsen et al., 2015).

Differences in levels of education between classes broadly support findings from a recent LCA study amongst nightlife attendees in New York (F. Fernández-Calderón et al., 2018), in that all polydrug using groups had a higher proportion of those achieving a university degree or higher than non-polydrug using classes. Similarly, the highest proportion of university graduates was observed in the *Moderate polydrug use* class. The link between university attendance and experimenting with wider drug use is well documented (Barrett et al., 2006; Webb, Ashton, Kelly, & Kamali, 1996), thus it may be that those who engage with the electronic dance music scene are more likely to continue these patterns of use following university.

The *Moderate* and *High polydrug use* classes attended on average more events in the past 12 months than the *Low polydrug use* class and the two non polydrug using classes, in support of associations between polydrug use and engaging with the electronic dance music scene (Hunt et al., 2009; Sanudo et al., 2015). However, while Sanudo et al (2015) found that attendance at electronic dance music clubs increased the odds of belonging to the “High level polydrug use” relative to the “No polydrug use” class, they aimed to include venues that were broadly representative of the scene in São Paulo as a whole (Sanudo et al., 2015), rather than focusing on a particular genre, while LCA studies amongst those engaging with the electronic dance music scene did not examine associations between attendance frequency and class membership (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017; Ramo et al., 2010). As our sample was restricted to those engaging with this particular genre, differing frequencies of attendance amongst latent classes may reflect distinct patterns within electronic dance music culture. For example, the observation that the *Cannabis use* class attended on average more events (18.57) in the past 12 months

than the *Low polydrug use* class (15.85) was not in the expected direction, and thus may point to a subset of regular party-goers who only use alcohol, tobacco and cannabis.

3.4.3 Wellbeing

In the first investigation of its kind amongst a nightlife population, differences in wellbeing were observed amongst polydrug use classes, as indexed by WHO-5 scores. Adjusting for age, gender, country of residence, education and event attendance, membership of the *Cannabis use*, *Moderate polydrug use* and *High polydrug use – hallucinogens/medication* classes was associated with significantly lower WHO-5 scores in comparison to the *No illicit use* class, indicating poorer well-being. While no association was found for the *High polydrug use – stimulants* class, the *Low polydrug use* class had higher average WHO-5 scores compared to the *No illicit use* class when controlling for demographic differences. The higher well-being scores amongst members of the *Low polydrug use* class, and the fact that the lowest scores were observed in the *Cannabis use* class, seemingly contradict previous LCA findings that polydrug use classes are associated with poorer mental health outcomes (Lynskey et al., 2006; Quek et al., 2013), although these studies were not conducted in nightlife populations. Furthermore, not all previous LCA studies examining polydrug use and mental health have associated increasing levels of use with worse outcomes. Morley et al (2015) did not find increasing risk of a depression or anxiety diagnoses in classes characterized by higher levels of polydrug use, but found that members of the “Cannabis and medication” class (characterized by use of cannabis, benzodiazepines and prescription opioids) had elevated odds of a diagnosis of anxiety. Interestingly, the class in our study with the lowest well-being scores was characterized by the use of cannabis and no other illicit drug. However, of the four polydrug using classes that also had high probabilities of past year cannabis use, only the *Moderate* and *High polydrug use – hallucinogen/medication* classes had lower WHO-5 scores relative to the *No illicit use* class. Whether drug use patterns typified by just cannabis result in poorer mental health (or vice versa) warrants further investigation, and should consider additional factors such as quantity and frequency of use. The higher well-being scores observed in the *Low polydrug use* class also requires further research, as this has not been found in previous LCA studies. It may be that this class represents a group that are more open to new experiences than the *No illicit use* class, but whose drug use does not reach levels that negatively impact on their mental health. For example, it may be that use of ecstasy alongside minimal use of other drugs in a nightlife context is related to increased quality of life. This cannot,

however, be assessed in the current study as drug use specifically within nightlife settings was not assessed, and so remains speculative at this stage.

Although statistically significant differences between classes were found with respect to WHO-5 scores, regression coefficients indicate that these differences were not large. WHO-5 indexes well-being on a scale from 0 to 100, and the largest difference observed was the *Cannabis use* class that was associated with a score just under 5 points lower than the *No illicit use* class when controlling for socio-demographic traits. Although intended to measure change within individuals, it is recommended that a 10% change in score is indicative of clinically significant change (WHO, 1998). A 5 point change as a percentage of the mean score amongst the *No illicit use* group is 7.89% $((5/63.4)*100)$, raising questions about how meaningful these differences are in terms of state well-being. Indeed, it may be that the WHO-5 is not a sensitive enough measure to truly elucidate meaningful differences amongst this population, and future research into the link between polydrug use patterns and mental health should incorporate additional measures.

3.4.4 Problematic alcohol consumption

Compared to the *No illicit use* class, all drug using classes were associated with higher AUDIT-C scores, indicative of a relatively higher risk of alcohol related harm. Examination of the regression coefficients (Table 3.3; Figure 3.6) shows that each drug using class was associated with an average AUDIT-C score at least 1.07 points higher than the *No illicit use* class, adjusting for socio-demographic characteristics. When considering that the raw mean AUDIT-C score of the *No illicit use* class was 3.8, this increase would put all other classes above the cut-off of 4 that suggests increased risk of alcohol related harm (Bush et al., 1998).

This is the first time that this relationship has been demonstrated amongst a population of young adults engaging with the nightlife scene, and supports findings from nationally representative samples showing an increase in problematic alcohol consumption to be associated with polydrug use (Armour et al., 2014; Smith et al., 2011). While the observed difference was most pronounced for the *Moderate polydrug use* class, suggesting this group may have the riskiest alcohol consumption patterns, the sample as a whole had an average AUDIT-C score above the cut off indicating increased risk of harm (Table 3.1). Indeed, the proportion of the sample as a whole that reached the AUDIT-C cut off score suggesting an increase in alcohol related harm was 80.96%, and while class differences were also

observed, the lowest proportion found in the *No illicit use* class was still almost 60%. This suggests that young European nightlife populations may benefit from universal harm reduction messages concerning alcohol use, such as those advocating alternating alcoholic with non-alcoholic drinks.

3.4.5 Problematic drug use

Elevated rates of problematic drug use, as indexed by average DUDIT scores, were seen in all latent classes relative to the *No illicit use* class. Adjusted regression coefficients (Table 3.3; Figure 3.7) indicate that class membership and DUDIT scores followed a ‘dose-response’ pattern, with more extensive polydrug use associated with higher mean scores, similar to findings by Ramo et al (Ramo et al., 2010). While no class reached a mean score of 25 that is taken to indicate heavy dependence on drugs (Berman et al., 2005), adjusted coefficients associate all classes, with the exception of *Cannabis use*, with an increase in DUDIT score relative to the *No illicit use* class of greater than 6 points, which is the cut off used as showing possible drug related problems. As such, according to the DUDIT, members of all four polydrug using classes displayed patterns of use that might be diagnosed as harmful use, substance abuse or possible dependence (Berman et al., 2005). The *High polydrug use – hallucinogens/medication* class had the highest DUDIT score, over and above that of the *High polydrug use – stimulants* class. This suggests that a polydrug use repertoire including hallucinogens, benzodiazepines and to a lesser extent prescription opioids may be associated with a greater degree of problematic use. It must be noted, however, that latent class membership in this study is based solely on past 12 month use of different drugs, whereas problematic use and dependence are likely to be influenced by other drug use behaviours, such as frequency and quantity of use. As such, future research into problematic use and dependence amongst those engaging with the nightlife scene should take such considerations into account.

3.4.6 Strengths and limitations

The limitations inherent to the design of the EMSS will be discussed in Chapter 6. There are, however, strengths and limitations that are specific to this study.

One strength of this particular study was the use of LCA to identify discrete polydrug use profiles, and the ability to confirm the discriminant validity of the chosen solution.

Therefore, findings underscore the utility of this approach in identifying heterogeneous patterns of substance use amongst nightlife populations. Furthermore, this is the first study

to use this method amongst a sample of young European adults engaging with the nightlife scene from more than one country. This is also the first study using this method to explore associations between patterns of use and mental health, and problematic alcohol and drug use amongst this population.

Despite these strengths, there are limitations that need to be considered when interpreting these results. For the purpose of this study, polydrug use was operationalised as the use of multiple substances in the past 12 months (Connor et al., 2014; Martin, 2008). Participants were not asked about their concomitant use of drugs, therefore we cannot confirm that drugs were used in combination, nor that drug use occurred in the context of nightlife settings. However, polysubstance users reporting past 12 month use have also been found to be highly likely to use in combination (Quek et al., 2013). Furthermore, we did not explore additional aspects of drug use such as frequency, quantities or routes of administration, which should be considered in future research investigating polydrug use in nightlife populations.

The decision to use binary past 12 month as polydrug use indicators was taken to allow comparison with the four existing LCA studies in nightlife populations in different settings. However, it must be acknowledged that a binary approach is likely to miss finer complexities in drug use patterns, particularly with regard to frequency. However, limitations with the way frequency was captured in the EMSS precluded inclusion of frequency in this initial investigation into drug use profiles. Specifically, LCA models using the seven frequency categories for each drug as latent indicators failed to reach a global solution due to their over complexity. Furthermore, that the frequency scale was non-linear means differences in average scores between groups would be close to impossible to meaningfully interpret.

While the use of standardised scales allows for comparability with other studies utilising the same measures, which was a key consideration of a number of ALAMA-Consortium members involved in wider projects, there are potential limitations associated with their use amongst the EMSS study population. For instance, the DUDIT was designed and initially validated for use within a clinical sample of heavy users in treatment, prison and probation settings. It is not unreasonable to suggest that patterns of use within a young adult sample of nightlife attendees will differ from this population, which questions the validity of the use of the DUDIT to accurately assess problematic drug use among EMSS participants.

Beyond the potential inability to reveal clinically significant differences between identified classes, the use of the WHO-5 as the sole index of mental health and wellbeing is a further limitation. Given that the WHO-5 assesses wellbeing state in the previous two weeks, our data collection period during summer may have confounded estimates and thus is arguably a too short term assessment of wellbeing. Additional measures may have helped corroborate findings between polydrug use and mental health, but unfortunately, while the PHQ2 and GAD2 were included in follow-up, they were not included in the baseline survey and thus could not be included in this study. Furthermore, with hindsight, a measure of previous mental health diagnosis would have helped elucidate this association.

3.4.7 Conclusion

In the first study to use LCA amongst young adults regularly engaging with the European nightlife scene in multiple countries, six distinct polydrug use profiles were identified. Different patterns were not simply defined in terms of using an increasing number of drugs in the past 12 months, highlighting the considerable heterogeneity in polydrug use in this population. The discriminant validity of these profiles was confirmed as classes differed on all demographic characteristics. After controlling for demographic traits, class differences were found with respect to well-being and problematic alcohol and drug use. Although the relationship with well-being was less clear, all drug using groups were associated with an increased risk of hazardous alcohol consumption and problematic drug use. The *High polydrug use – hallucinogens/medication* class were found to be at most risk of possible substance abuse and dependence. The considerable heterogeneity in polydrug patterns highlights the need to tailor prevention and harm reduction strategies accordingly. Highlighting which profiles are most associated with riskier use patterns and possible dependence allows the identification of key targets for such interventions.

Chapter 4: Harm reduction behaviours and associations with negative consequences and positive experiences amongst polydrug users regularly attending the European nightlife scene

4.1 Introduction

The association between the electronic dance music scene and drug use is well established (e.g. Winstock et al., 2001). Elevated rates of use amongst those attending nightclubs and festivals are thought to place this population at greater risk of harm, compounded by polydrug use (Groves et al., 2009) and environmental factors such as the risk of dehydration and overheating from physical exertion (Parrott, 2012; Parrott & Young, 2014).

There is evidence that drug users are aware of these risks, and thus employ a range of protective behavioural strategies in an attempt to reduce the chance of negative consequences resulting from their use. Furthermore, studies have shown that employing harm reduction strategies is associated with experiencing fewer negative outcomes following the use of certain substances. For example, the use of alcohol related harm reduction strategies such as alternating alcohol and non-alcoholic drinks, avoiding drinking games and stopping at a certain time have been associated with experiencing fewer negative experiences (Benton et al., 2004; Martens et al., 2004) and lower scores on the Rutgers Alcohol Problem Index (Bravo, Prince, & Pearson, 2017; Martens et al., 2005; Martens, Pederson, LaBrie, Ferrier, & Cimini, 2007).

Studies investigating harm reduction behaviours amongst cannabis users have found similar results. Pedersen and colleagues (2016) developed a 39-item measure of cannabis harm reduction behaviours that included strategies such as avoiding using early in the day, taking a break if feeling low in motivation, avoiding using concentrated forms and taking breaks to decrease tolerance. Amongst a sample of university students in North America, mean scores on the so-called Protective Behavioural Strategies for Marijuana scale (PBSM) were negatively correlated with mean Cannabis Use Disorder Identification Test (CUDIT; $r = -0.47$) and Brief Marijuana Consequence Questionnaire (B-MACQ; $r = -0.33$) scores. This negative

relationship between PBSM scores and negative consequences was also shown by Bravo and colleagues (2017) using the full Marijuana Consequences Questionnaire (MACQ) in a separate sample of North American university students. Furthermore, women were found to be more likely to employ harm reduction strategies and experience fewer cannabis related negative consequences (Bravo, Prince, Pearson, et al., 2017).

With regard to substances that are perhaps more widely considered as ‘club drugs’ such as ecstasy, evidence from qualitative studies shows that users adopt a variety of strategies in the belief that they mitigate against potential harm (Jacinto, Duterte, Sales, & Murphy, 2008; Kelly, 2009; Panagopoulos & Ricciardelli, 2005). Results from quantitative studies suggest that such practices may in fact be widely endorsed. For example, in an online survey of 184 recent ecstasy users in the UK and USA at least 75% of participants endorsed use of eleven out of nineteen strategies, including using only when in a good mood, buying from a trusted source and rehydrating to replace lost fluids (Davis & Rosenberg, 2017).

One specific harm reduction strategy that ecstasy users sometimes cite as using to combat ecstasy related depression in the days after use is pre- or post-loading. This practice refers to taking, for example, serotonergic substances such as 5-Hydroxytryptophan (5-HTP), herbal supplements, vitamin C and foodstuffs rich in tryptophan such as milk or turkey, either pre or post ecstasy use (Kelly, 2009). Evidence from one study amongst Australian past year ecstasy users suggests this may be frequently employed, with 41% and 47% of the sample endorsing pre- and post-loading respectively (Allott & Redman, 2006).

Despite evidence suggesting that employing harm reduction strategies is a common practice amongst ecstasy users, to the author’s knowledge only one study has investigated whether this is related to negative experiences associated with use. Using an online survey of 594 past year ecstasy users living in Spain, Vera et al (2018) explored the associations between the use of seven harm reduction strategies (buying from a reliable source; planning use sessions instead of taking what is offered; taking smaller rather than larger doses; spacing out use sessions and parties; setting limits on quantities used and trying not to exceed them; avoid mixing stimulants; waiting for the effect of a dose to decrease before taking another) and twelve negative consequences of ecstasy use. In line with findings from other surveys (Allott & Redman, 2006; Davis & Rosenberg, 2017), the use of harm reduction strategies was widespread: over half the sample endorsed each strategy, with the exception of waiting for the effects to decrease before re-dosing (42.8%), either “sometimes”, “almost always” or “always”, with the most commonly employed being

buying from a reliable source (79.2%), planning sessions (64.7%) and taking small doses (63.8%).

Comparing high frequency (defined as using a harm reduction strategy “nearly always” or “always”) with low frequency (employing a strategy “never”, “nearly never” or “sometimes”) groups for each strategy, Vera and colleagues (2018) found preliminary evidence of a protective effect for four strategies, in that the high frequency group had significantly lower odds of experiencing one or more of twelve negative effects. The strategy that showed the strongest association with negative experiences was planning use sessions instead of taking what was offered, with lower odds observed for the high frequency group for five out of twelve consequences. The strategies spacing out use sessions and parties, waiting for the effect of a dose to decrease before taking another and setting limits on quantities used showed more moderate associations, with each showing lower odds for the high frequency group for two negative consequences.

There is also preliminary evidence that employing harm reduction strategies is associated with lower probabilities of experiencing negative consequences of ketamine use. In a study of 462 past year recreational ketamine users (Vidal Gine, Fernández-Calderón, & Lopez Guerrero, 2016), the most frequently employed harm reduction strategies were spacing out sessions (60.8% responded “almost always” or “always”), spacing out doses within a session (54.5%) and setting limits to the amount used (41.3%). Frequent use of the strategy spacing out doses within a session was associated with lower probabilities of experiencing memory impairment, abrupt changes in mood and sleeping problems. Participants who frequently avoided combining ketamine with other substances had significantly lower odds of experiencing six out of eight negative consequences. However, only 25.9% of participants said that they always or almost always employed this strategy.

Given that drug users engaging with the nightlife scene are typically polydrug users and thus thought to be at greater risks of harm (see Chapter 3), establishing whether harm reduction strategies are effective at reducing these risks is particularly important amongst this population. In-depth interviews with young adults regularly attending the electronic dance music scene have shown that polydrug users do adopt a range of harm reduction strategies (Hunt et al., 2009; Van Havere et al., 2015).

Indeed, Fernández-Calderón et al (2014) found that amongst 252 polydrug using underground rave attendees harm reduction strategies were common, with over 50% of

participants reporting almost always or always using seven of sixteen strategies (alternating nostrils when snorting; pausing when dancing to take a rest; hydrating with water, soft drinks or isotonic drinks; avoiding consuming with strangers or in unfamiliar environments; buying drugs from reliable sources; completely powdering drugs before snorting; taking a good rest after the party). The strategies that participants most widely endorsed using always or almost always were resting after the party (77.9%), completely powdering drugs when snorting (75.2%), drinking water to avoid dehydration (73.9%) and buying from reliable sources (69.1%). The strategies that had the highest proportion of participants reporting never or almost never employing were analysing or testing drugs beforehand (79.9%), avoiding mixing drugs with alcohol (73.5%), and avoiding mixing depressants (59.9%) and stimulants (56.6%). That strategies around avoiding combining drugs were amongst those least endorsed is not surprising amongst this sample, although perhaps suggest that polydrug use should be considered in terms of use of multiple substances at the same time, rather than the use of different drugs on separate occasions over a given time period. The likelihood of always or almost always employing harm reduction strategies was influenced by polydrug use, in that those identified as high polydrug users (defined as use of six or more drugs in the past month) were less likely to endorse eight of the 16 strategies than low polydrug users. However, Bonferroni corrected p-values suggest that the only significant differences between polydrug using groups were found for taking a test dose when the purity was unknown and avoiding or being careful about mixing depressants.

To the author's knowledge, only one study has investigated the relationship between harm reduction strategies and self-reported negative consequences amongst polydrug using nightlife attendees. Past year festival attendees, who had also used two or more drugs in the past year ($n=1126$), participated in an online survey examining the association between six harm reduction strategies conceptualised as 'dosing' related (set limits on quantities used; take smaller doses instead of larger doses; wait for the effects of a dose to decrease before re-dosing; avoid mixing depressants; avoid mixing stimulants; use lower quantity when combining drugs) and experiencing thirteen negative consequences of drug use in the past 12 months (Fernández-Calderón, Díaz-Batanero, Barratt, & Palamar, 2019).

Initial analyses suggested that high frequency use (always or almost always) of each dosing related strategy was associated with reporting significantly fewer negative consequences. The strongest relationship was observed for setting limits on quantities used, with the high

frequency group experiencing ten of thirteen consequences significantly less often than the low frequency group (Fernández-Calderón et al., 2019). However, the strength of this association was substantially attenuated when adjusting for age, gender and type of drug use in the past 12 months, with fewer significant differences resulting from multivariate logistic regression models. For example, the strategy of taking smaller instead of larger doses was associated with six consequences in bivariate analyses, but none in multivariate models. Avoiding mixing depressants almost or always almost was associated with experiencing five consequences significantly less frequently than not doing so, the most of any strategy. Four negative consequences were similarly associated with setting limits on the quantities used, three with avoiding mixing stimulants and one for both waiting for the effects to decrease before re-dosing and using lower quantities when combining drugs (Fernández-Calderón et al., 2019).

All strategies were endorsed almost always or always by over half the sample, with the exception of waiting for the effects to reduce before re-dosing (47.8%), contributing to existing evidence that harm reduction is a widespread practice amongst this population. Gender differences were found in that males were less likely to take small test doses and to wait before re-dosing (Fernández-Calderón et al., 2019), consistent with previous findings that females are more likely to endorse harm reduction strategies (Akram & Galt, 1999; Benton et al., 2004). Furthermore, stimulant users were found to adopt five out of six strategies significantly less frequently than participants who did not use stimulants in the past 12 months. Conversely, those who used any new psychoactive substance were more likely to employ four out of six strategies than those who did not (Fernández-Calderón et al., 2019).

The study by Fernández-Calderón et al (2019) provides important preliminary evidence that the use of certain harm reduction strategies is associated with experiencing fewer negative consequences of polydrug use. However, it is limited by the fact that the relationship between negative consequences and harm reduction was only explored in the context of the use of six behavioural strategies. A number of other strategies have been found to be utilised during drug use in an attempt to mitigate against harm, such as avoiding combining with alcohol, taking rests from physical activity and keeping hydrated. It has also been shown that a range of strategies are adopted both before use (for example, pre-loading, obtaining drugs from a reliable source and planning when to take drugs during the session) and after use (such as post-loading, taking regular breaks from use and catching up on lost

sleep). There is, therefore, an urgent need for an investigation into how a more comprehensive range of behaviours are associated with negative outcomes, as this might better reflect drug users' overall approach to adopting harm reduction strategies.

There is also a lack of empirical research into whether harm reduction strategies are related to positive experiences of drug use. To the author's knowledge, the only relevant research to date is the 'High-Way Code', in which drug users participating in the Global Drug Survey were asked whether different harm reduction strategies increased, decreased or had no effect on the pleasure they perceived from use of the drug (GDS, 2014). Very few participants stated that any of the harm reduction strategies decreased their pleasure from drugs, and a high proportion in fact stated that use of a number of strategies increased their pleasure. For example, 54% and 49% of MDMA and stimulant users respectively reported having a more pleasurable experience when they avoided using when feeling anxious or depressed, while 63% of ketamine users who planned their session in advance stated that this increased their pleasure. Given that use of drugs in the nightlife scene appears to be primarily motivated by their perceived positive effects (Ter Bogt & Engels, 2005), testing whether harm reduction strategies are associated with pleasurable experiences would be important for promoting behaviours and interventions that may mitigate the risk of drug use.

Furthermore, despite evidence showing that harm reduction strategies differ in terms of how universally they are adopted, no study has considered whether underlying subgroups of individuals exist who employ different patterns with regard to which strategies they employ. Indeed, it seems reasonable to suggest that the adoption of certain strategies might be associated with higher probabilities of utilising others.

Latent class analysis (LCA) is a statistical method used to identify hidden subgroups of people that are similar to each other with respect to a set of observed behaviours or attributes. This technique has been widely adopted for a number of reasons in various populations, including for the identification of polydrug use profiles amongst nightlife attendees (F. Fernández-Calderón et al., 2018; Hannemann et al., 2017; Ramo et al., 2010; Sanudo et al., 2015). However, no attempts have previously been made to apply LCA to harm reduction behaviours to investigate how the use of different strategies may co-occur in different groups of people. Applying this technique to a range of harm reduction behaviours could, for example, offer a way to identify which groups show the highest level

of vulnerability or resilience to drug related harms, in order to use prevention, harm reduction and treatment strategies in a targeted manner.

In order to address these gaps in the harm reduction literature, this Chapter has three objectives:

1. Employ latent class analysis to characterise the different patterns of the past 12 month use of harm reduction strategies in a sample of polydrug using young adults engaging with the European nightlife scene.
2. Build on findings in Chapter 3 to assess the relationships between harm reduction patterns and different profiles of polydrug use identified by a previous latent class analysis.
3. Use exploratory factor analysis to identify subscales of positive and negative experiences following drug use, and investigate their relationship with harm reduction patterns.

4.2 Methods

4.2.1 Participants

Participants in this study were completers of the baseline Electronic Music Scene Survey (EMSS) conducted in 2017. The EMSS development, design and recruitment strategies are discussed in Chapter 1, so will not be repeated. In addition to the project inclusion criteria, the sample for this study was restricted to polydrug users, as defined by membership to one of the four polydrug using classes identified by latent class analysis in Chapter 3. Of these 4,223 participants, 27 had missing data for harm reduction variables thus were excluded from this study, resulting in a final sample size of 4,196.

Ethical approval in the UK was provided by the UCL Research Ethics Committee (10437/001).

4.2.2 Measures

4.2.2.1 ALAMA Harm Reduction Scale

A list of 30 strategies that might be employed before, during and after drug use was developed by members of the ALAMA-Consortium. The ALAMA consortium includes an international panel of experts on drug use and the nightlife scene consisting of academics, clinicians and nightlife harm reduction service providers from five countries (Belgium, Italy, the Netherlands, Sweden and the UK). During the survey, EMSS participants were asked *“In the last 12 months have you implemented any of the following strategies to minimise potential harms from drug use in relation to an electronic dance/ electronic music event?”* Participants responded “Yes” or “No” to each of the following items:

Before use:

1. Research new drugs or pills online.
2. Test your drugs using a home testing kit or testing service.
3. Get advice on new drugs or batches from a trusted prior user.
4. Plan what you would do if you or your friends start to feel unwell.
5. Make prior arrangements about how you will get home.
6. Take pre-loading substances with the aim of preparing for drug use, such as multivitamins, 5-HTP...
7. Avoid using if you are depressed, anxious or going through a rough patch.
8. Eating properly/well before use.
9. Have a healthy day before going out.
10. Plan when to take drugs during the evening.
11. Plan how to get drugs into venue(s).
12. Set limits on the amount that you use

During use:

1. Take a small test dose of a new drug, new batch or drug that you do not know the purity of.
2. Only use drugs that you have sourced from a trusted dealer or friend.
3. Tell someone what you have taken.
4. Keep an eye on your friends and others.
5. Drink a safe amount of water.
6. Avoid combining illicit drugs and/or alcohol.

7. Take regular breaks from physical activity, such as dancing, to 'chill out'.
8. Avoid sharing tubes/straws/notes/keys/cards when sniffing.
9. Avoid using drugs intravenously.
10. Chewing candy or gum to avoid teeth grinding.
11. Keeping your drug use in line with what you would consider 'normal' (i.e. recreational, sensible and controlled).

After use:

1. Eat properly/well on the morning/day after use.
2. Taking post-loading substances with the aim of recovering and/or dealing with hangovers/comedowns, such as multivitamins, 5-HTP, fruit juice, milk, sleeping tablets.
3. Take regular breaks from drug use.
4. Avoid driving under the influence.
5. Maintaining a healthy lifestyle, with regard to sleep, exercise and diet.
6. Catching up on lost sleep.
7. Contact friends the next day to see if they are ok.

4.2.2.2 Polydrug use

Polydrug use was defined as belonging to one of the four polydrug use classes that were identified by latent class analysis in Chapter 3. Levels of polydrug use are thus classified as follows: "Low polydrug use"; "Moderate polydrug use"; "High polydrug use – stimulants"; "High polydrug use – hallucinogens/medication".

4.2.2.3 ALAMA Positive and Negative Drug Use Experiences Scale

The ALAMA-Consortium compiled a list of eight positive and 22 negative experiences that could potentially occur as a result of drug use. EMSS participants were asked how often they experienced each of the 30 items in the past 12 months on a scale of 0 "Never" to 10 "All the time". In order to determine which items were measuring the same construct and thus create subscales, factor analysis was conducted on responses to these items and composite scores created for emergent factors (see Statistical analysis below).

4.2.2.4 Socio-demographic characteristics

All participants provided their age, country of residence (Belgium; Italy; Netherlands; Sweden; UK), gender (Male; Female; Other) and highest level of education (each countries

equivalent of UK levels: Key stage 1 and 2; Key stage 3; Key stage 4; University degree or higher). Participants were also asked how many electronic dance music events they attended in the past 12 months.

4.2.3 Statistical analysis

4.2.3.1 Latent Class Analysis (LCA) of harm reduction profiles

LCA was used to identify distinct subgroups of polydrug users who differed in their patterns of past 12 month endorsement of various harm reduction strategies. A thorough discussion of the concepts behind LCA can be found in Chapter 3. Using the 30 harm reduction strategies as binary indicator variables, models ranging from one to ten latent classes using maximum likelihood and multiple starting values were sequentially fit and examined to identify the number of classes that best explained the data. In determining the best fitting model, fit indices Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and sample size adjusted Bayesian Information Criterion (aBIC) were examined, along with the Lo-Mendell-Rubin adjusted likelihood ratio test, entropy values, class sample size and theoretical interpretation of the different solutions. Latent class enumeration was conducted in Mplus version 8.2 (Muthén & Muthén, 2018).

4.2.3.2 Factor analysis of drug use experiences

Exploratory Factor Analysis (EFA) with maximum likelihood estimation and Geomin rotation was conducted in order to identify similar groupings of experiences to create subscales to be used as outcome measures in further analyses. Models postulating two to ten factors were fit on the 30 drug use experience variables. Models with eigenvalues greater than one were examined in more detail, along with the plot of each eigenvalue as an additional factor is estimated ('scree plot'). To determine the optimum number of factors, the Geomin rotated factor loadings were examined for each factor, with loadings greater than 0.40 indicating convergent validity and the absence of strong cross loadings showing discriminant validity of factors. Cronbach's alpha scores for identified factors were also calculated as a measure of internal reliability. Additionally, as with LCA, the theoretical interpretation of the differing models was considered when deciding the final solution.

Composite scores for the emergent factors were created by calculating the mean score of items within each factor. This resulted in composite scores ranging from 0 to 10, with higher scores indicating more frequent experience following drug use.

Factor analysis and the creation of composite outcome scores were conducted in Mplus version 8.2 (Muthén & Muthén, 2018).

4.2.3.3 Associations between harm reduction profiles and drug use experiences

The discriminant validity of the chosen latent class solution was assessed by omnibus ANOVA tests on age and number of events attended in the past 12 months, while chi-square omnibus tests were conducted on country of residence, gender and education.

As discussed in Chapter 3, assigning participants to latent classes using a modal approach and thus treating the latent variable as manifest in analysis does not account for classification error, which can lead to biased estimates. To account for this classification error, regressions with experience subscales as the outcome were attempted using the BCH method (Asparouhov & Muthén, 2014b; Bolck et al., 2004). However, models failed to converge producing untrustworthy estimates as a result of negative weights. As a result, regressions using the ML 3-step method (Vermunt, 2010) were attempted, but class proportions changed substantially when introducing outcomes and covariates to regression models in the third step.

As such, participants were assigned latent class membership using proportional assignment (Bakk et al., 2013; Bakk & Vermunt, 2016; Goodman, 2007). This involved entering latent class membership probabilities as independent variables in linear regressions models with experience subscale scores as outcome variables. Final models were adjusted for class differences in gender, age, country of residence, educational level and attendance at electronic dance music events. These analyses were conducted in SPSS version 25 (IBM Corp, 2017).

4.3 Results

4.3.1 Sample characteristics

The characteristics of the 4,196 participants included in this study are shown in Table 4.1. The sample was two-thirds male, had an average age of nearly 24 and had high levels of education, with almost 90% having achieved the equivalent of GCSE / A-Level / key stage 4 or higher. As discussed in Chapter 3, polydrug using classes mainly consisted of participants resident in the UK or Netherlands, thus 73.50% of the sample for this study were resident in one of these two countries.

Table 4.1: Socio-demographic characteristics by harm reduction latent class and for sample as a whole

	Whole sample	Low HR before use	Moderate HR after use	High HR with loading	High HR no loading	Extensive HR throughout	Omnibus test
N (%)	4196 (100%)	459 (10.94%)	645 (15.37%)	852 (20.31%)	985 (23.47%)	1255 (29.91%)	
Age	23.86 (± 0.13)	24.76 (± 0.38)	22.83 (± 0.32)	24.74 (± 0.27)	23.64 (± 0.26)	23.65 (± 0.22)	F=12.47, p<0.001
Gender							
Male	67.06%	74.95%	69.77%	67.49%	66.40%	63.03%	$\chi^2=26.90$, p=0.001
Female	32.29%	24.62%	29.92%	32.04%	32.89%	36.02%	
Other	0.64%	0.44%	0.31%	0.47%	0.71%	0.95%	
Country of residence							
Belgium	9.82%	19.17%	11.47%	5.63%	14.01%	5.10%	$\chi^2=250.88$, p<0.001
Italy	3.93%	8.28%	4.19%	1.41%	6.60%	1.83%	
Netherlands	37.92%	27.89%	34.42%	45.07%	29.54%	45.10%	
Sweden	12.75%	15.90%	13.18%	10.68%	11.57%	13.71%	
UK	35.58%	28.76%	36.74%	37.21%	38.27%	34.26%	
Education							
Primary school / key stage 1 and 2	1.12%	1.75%	1.56%	0.59%	1.02%	1.12%	$\chi^2=92.82$, p<0.001
Secondary school / key stage 3	10.60%	13.35%	15.24%	6.60%	9.68%	10.62%	
GCSE / A-level / key stage 4	52.62%	47.70%	58.79%	47.41%	53.72%	53.91%	
University degree / NVQ4 or higher	35.66%	37.20%	24.42%	45.40%	35.58%	34.35%	

	Whole sample	Low HR before use	Moderate HR after use	High HR with loading	High HR no loading	Extensive HR throughout	Omnibus test
Events past 12 months	19.91 (± 0.53)	24.03 (±2.11)	21.95 (±1.68)	19.93 (±1.10)	18.71 (±0.99)	18.30 (±0.79)	F=12.47, p<0.001
Polydrug use class							
Low	30.58%	25.49%	22.17%	20.77%	40.51%	30.58%	χ ² =217.80, p<0.001
Moderate	37.04%	43.57%	39.07%	37.44%	40.51%	36.04%	
High – hallucinogens/ medication	19.92%	21.57%	26.67%	22.89%	11.68%	19.92%	
High – stimulants	12.46%	9.37%	12.09%	18.90%	7.30%	13.47%	
HR – Harm reduction; UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; F – ANOVA F test statistic; χ ² - chi-squared test statistic							

The proportion of participants endorsing each of the harm reduction strategies in the past 12 months is shown in Figure 4.1, while mean positive experience and negative consequence frequency scores are displayed for the sample as a whole in Table 4.2 and by gender in Table 4.3.

Figure 4.1: Past 12 month endorsement of harm reduction strategies before, during and after drug use

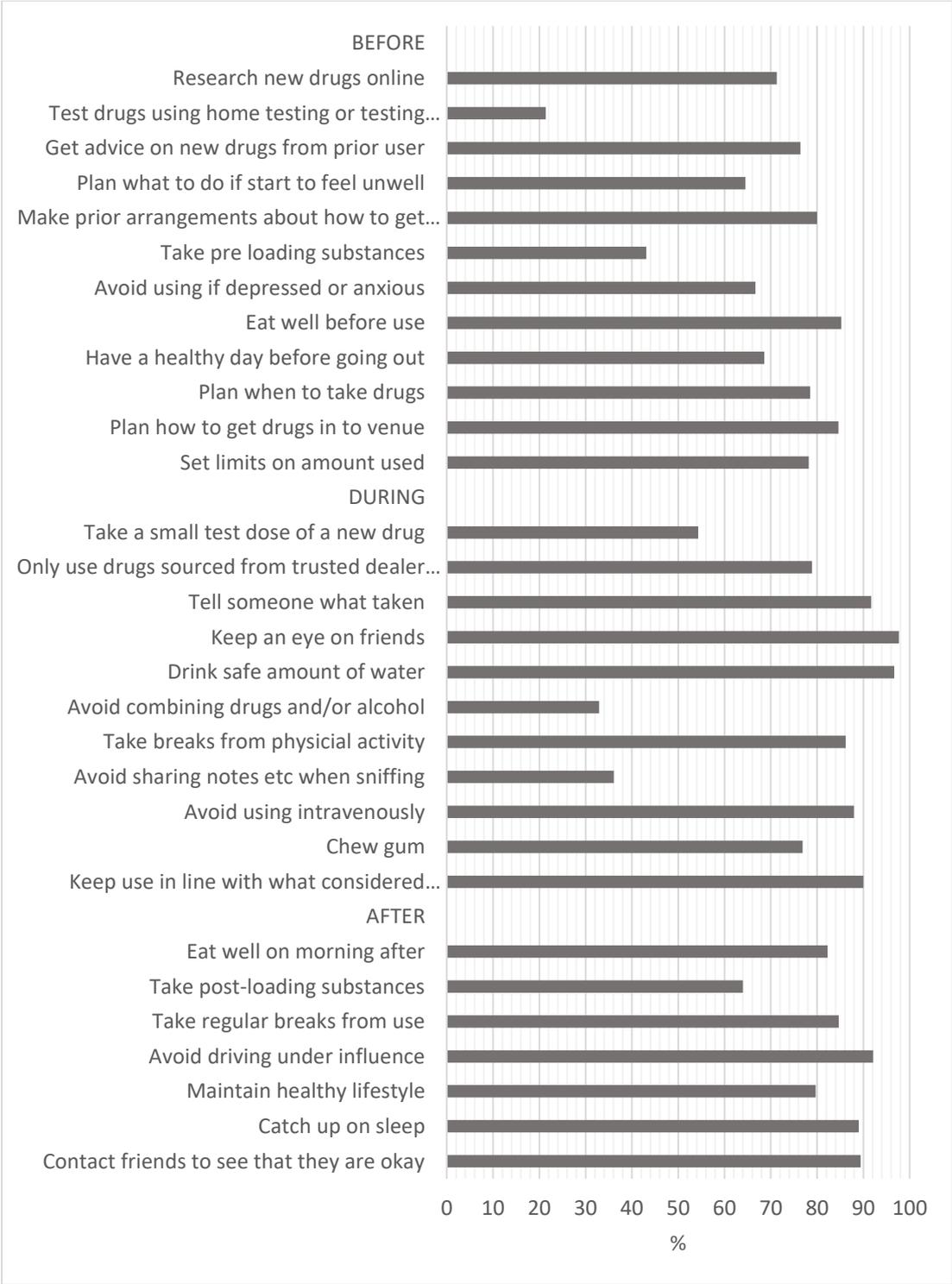


Table 4.2: Mean positive experiences and negative consequences frequency scores for sample as a whole

	Mean	(95% CI)
Positive experiences		
Intense pleasure	7.91	(7.85, 7.98)
Enhanced perception and increased enjoyment of music	8.19	(8.13, 8.25)
Reduced inhibitions	6.57	(6.48, 6.66)
Feelings of love and empathy	7.29	(7.21, 7.36)
Expanded consciousness	5.79	(5.70, 5.88)
Increased sense of enlightenment	5.50	(5.40, 5.60)
Closeness to others	6.77	(6.68, 6.85)
Making new friends	6.17	(6.08, 6.26)
Negative consequences		
Memory loss	2.97	(2.88, 3.06)
Vomiting	1.14	(1.08, 1.20)
Agitation	1.63	(1.56, 1.70)
Accidents	0.43	(0.39, 0.46)
Aggression/victim of aggression	0.34	(0.31, 0.37)
Breathing difficulties	0.48	(0.45, 0.52)
Panic attacks/anxiety	0.99	(0.94, 1.05)
Arguments with friends	0.37	(0.33, 0.40)
Overheating	1.33	(1.27, 1.40)
Fainting/collapsing	0.16	(0.13, 0.18)
Inability to move	0.34	(0.31, 0.38)
Sexual activity you later regret	0.45	(0.41, 0.49)
Driven/been driven by someone under the influence	0.90	(0.85, 0.96)
Palpitations	0.64	(0.59, 0.68)
Low mood/anxiety in days after use	1.18	(1.12, 1.24)
Problems with a bouncer (e.g. drugs confiscated)	2.88	(2.80, 2.87)
Legal problems (e.g. being arrested)	0.34	(0.31, 0.37)
Seeking/receiving emergency medical treatment	0.14	(0.12, 0.17)
Spending money you cannot afford to	0.13	(0.11, 0.15)
Effect of the drug not as expected	1.32	(0.25, 1.39)
Problems with sleep in days after use	1.06	(1.01, 1.12)
Missing work or other important commitments	1.81	(1.74, 1.89)

Table 4.3: Mean positive experience and negative consequence frequency scores by gender

	Mean	Male (95% CI)	Mean	Female (95% CI)	t	p
Positive experiences						
Intense pleasure	7.94	(7.86, 8.02)	7.90	(7.78, 7.78)	0.55	0.579
Enhanced perception and increased enjoyment of music	8.22	(8.15, 8.30)	8.14	(8.03, 8.25)	1.20	0.231
Reduced inhibitions	6.55	(6.45, 6.66)	6.61	(6.46, 6.77)	-0.62	0.536
Feelings of love and empathy	7.20	(7.10, 7.29)	7.48	(7.36, 7.61)	-3.57	<0.001
Expanded consciousness	5.73	(5.62, 5.85)	5.90	(5.74, 6.07)	-1.69	0.091
Increased sense of enlightenment	5.37	(5.26, 5.49)	5.78	(5.62, 5.95)	-4.01	<0.001
Closeness to others	6.69	(6.59, 6.79)	6.93	(6.79, 7.07)	-2.72	0.007
Making new friends	6.12	(6.01, 6.23)	6.28	(6.12, 6.44)	-1.67	0.094
Negative consequences						
Memory loss	3.02	(2.91, 3.12)	2.89	(2.73, 3.04)	1.40	0.161
Vomiting	0.94	(0.88, 1.00)	1.54	(1.42, 1.67)	-9.38	<0.001
Agitation	1.51	(1.43, 1.58)	1.88	(1.75, 2.01)	-5.15	<0.001
Accidents	0.43	(0.39, 0.47)	0.42	(0.36, 0.48)	0.25	0.802
Aggression/victim of aggression	0.34	(0.30, 0.37)	0.35	(0.30, 0.41)	-0.51	0.613
Breathing difficulties	0.41	(0.36, 0.45)	0.64	(0.56, 0.72)	-5.55	<0.001
Panic attacks/anxiety	0.89	(0.82, 0.95)	1.21	(1.10, 1.32)	-5.30	<0.001
Arguments with friends	0.37	(0.33, 0.40)	0.36	(0.30, 0.41)	0.22	0.830
Overheating	1.30	(1.23, 1.38)	1.39	(1.28, 1.51)	-1.27	0.204
Fainting/collapsing	0.14	(0.11, 0.16)	0.19	(0.14, 0.23)	-2.06	0.039
Inability to move	0.33	(0.30, 0.37)	0.36	(0.30, 0.42)	-0.81	0.420
Sexual activity you later regret	0.47	(0.42, 0.52)	0.39	(0.33, 0.46)	1.71	0.087

	Male		Female		t	p
	Mean	(95% CI)	Mean	(95% CI)		
Driven/been driven by someone under the influence	0.92	(0.85, 0.99)	0.87	(0.77, 0.97)	0.87	0.384
Palpitations	0.63	(0.58, 0.69)	0.65	(0.57, 0.74)	-0.47	0.642
Low mood/anxiety in days after use	1.05	(0.98, 1.12)	1.44	(1.33, 1.55)	-6.02	<0.001
Problems with a bouncer (e.g. drugs confiscated)	2.67	(2.57, 2.77)	3.35	(3.19, 3.51)	-7.46	<0.001
Legal problems (e.g. being arrested)	0.41	(0.36, 0.45)	0.21	(0.17, 0.25)	5.74	<0.001
Seeking/receiving emergency medical treatment	0.17	(0.14, 0.21)	0.08	(0.05, 0.11)	3.60	<0.001
Spending money you cannot afford to	0.12	(0.10, 0.15)	0.14	(0.10, 0.18)	-0.60	0.546
Effect of the drug not as expected	1.32	(1.23, 1.40)	1.35	(1.22, 1.47)	-0.41	0.683
Problems with sleep in days after use	1.00	(0.94, 1.07)	1.19	(1.09, 1.29)	-3.17	0.001
Missing work or other important commitments	1.71	(1.62, 1.80)	2.04	(1.91, 2.18)	-4.15	<0.001

Bonferroni corrected significant differences (0.05 / 30 = 0.0017) highlighted in bold

4.3.2 LCA of harm reduction strategies

4.3.2.1 Model selection

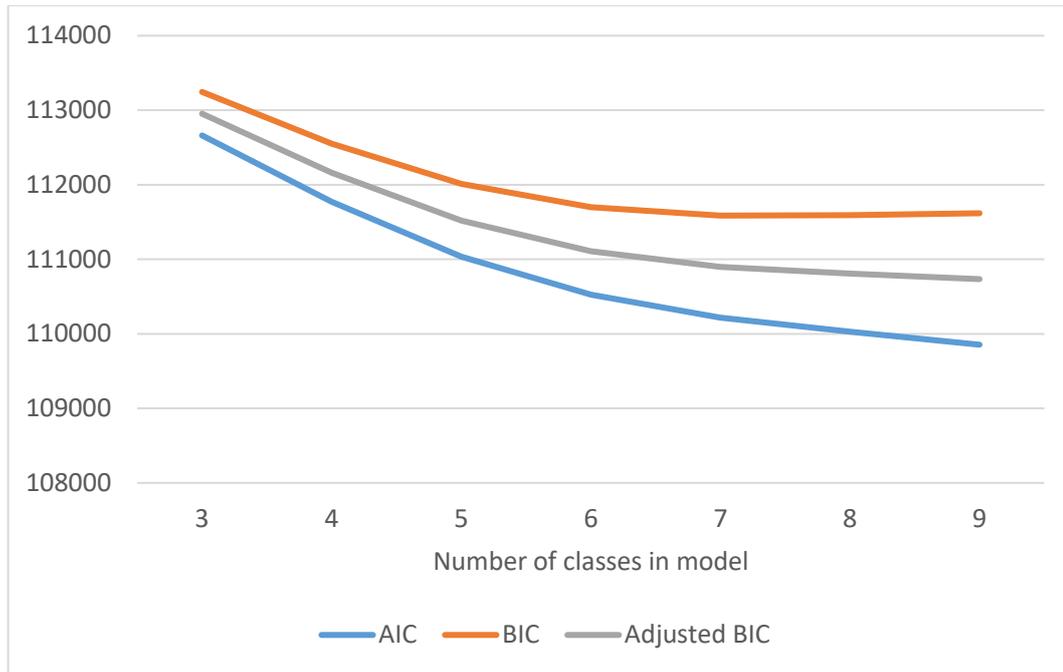
As with latent class model enumeration in Chapter 3, sequentially fitting one to ten latent classes failed to reach a global solution in that model fit indices continued to improve with each additional class (Table 4.4). The fit indices plot (Figure 4.2) indicated that the ‘elbow point’ at which the magnitude of the reduction reduces occurred when fitting the five class model, while the Lo-Mendell-Rubin adjusted likelihood ratio tests failed to reach significance for models fitting eight or more classes. As such, the theoretical interpretability of models postulating four to seven classes was examined. It was decided that a five class model offered the best solution, as extracting additional classes did not introduce substantively distinct harm reduction profiles over and above the five class model.

Table 4.4: Harm reduction LCA model fit indices for 1 to 10 class solution

Classes	AIC	BIC	Adjusted BIC	Entropy	LMR p-value
1	120226.203	120416.460	120321.132	-	-
2	113737.702	114124.557	113930.725	0.771	<0.0001
3	112661.828	113245.282	112952.945	0.747	<0.0001
4	111770.983	112551.036	112160.193	0.711	0.0005
5	111033.248	112009.899	111520.552	0.722	0.009
6	110524.189	111697.438	111109.586	0.727	0.021
7	110216.302	111586.150	110899.793	0.728	0.015
8	110027.022	111593.469	110808.607	0.729	0.122
9	109854.067	111617.112	110733.745	0.736	0.133
10	109699.383	111659.026	110677.155	0.743	0.547

Chosen 5 class solution highlighted in bold
AIC – Akaike Information Criterion; BIC – Bayesian Information Criterion; LMR – Lo-Mendell-Rubin

Figure 4.2: Plot of fit indices AIC, BIC and adjusted BIC



4.3.2.2 Harm reduction profiles

The probabilities of endorsing each of the harm reduction strategies within the five latent classes are plotted in Figure 4.3 with key defining characteristics displayed in Table 4.5, suggesting that profiles can be considered as follows:

1. *Low HR before use (10.94%)*: The class with the lowest probabilities of endorsing harm reduction strategies. Differences with other classes were most pronounced in strategies endorsed before and after use.
2. *Moderate HR after use (15.37%)*: Higher probabilities of strategy endorsement overall than *Low HR before use* class. With regard to strategies utilised before use, higher probabilities were observed in those related to planning and researching, while those related to maintaining general health had lower endorsement probabilities. Similarly, strategies related to general health after use had the lowest probabilities of past 12 month endorsement.
3. *High HR with loading (20.31%)*: The first of three classes with high probabilities of adopting the majority of harm reduction strategies. Low probabilities were observed for testing drugs. During use, taking a test dose of a new drug was endorsed with moderate probability, while low probabilities were observed for both avoiding combining drugs and avoiding sharing snorting paraphernalia.

Figure 4.3: Probability plot for harm reduction LCA five class solution

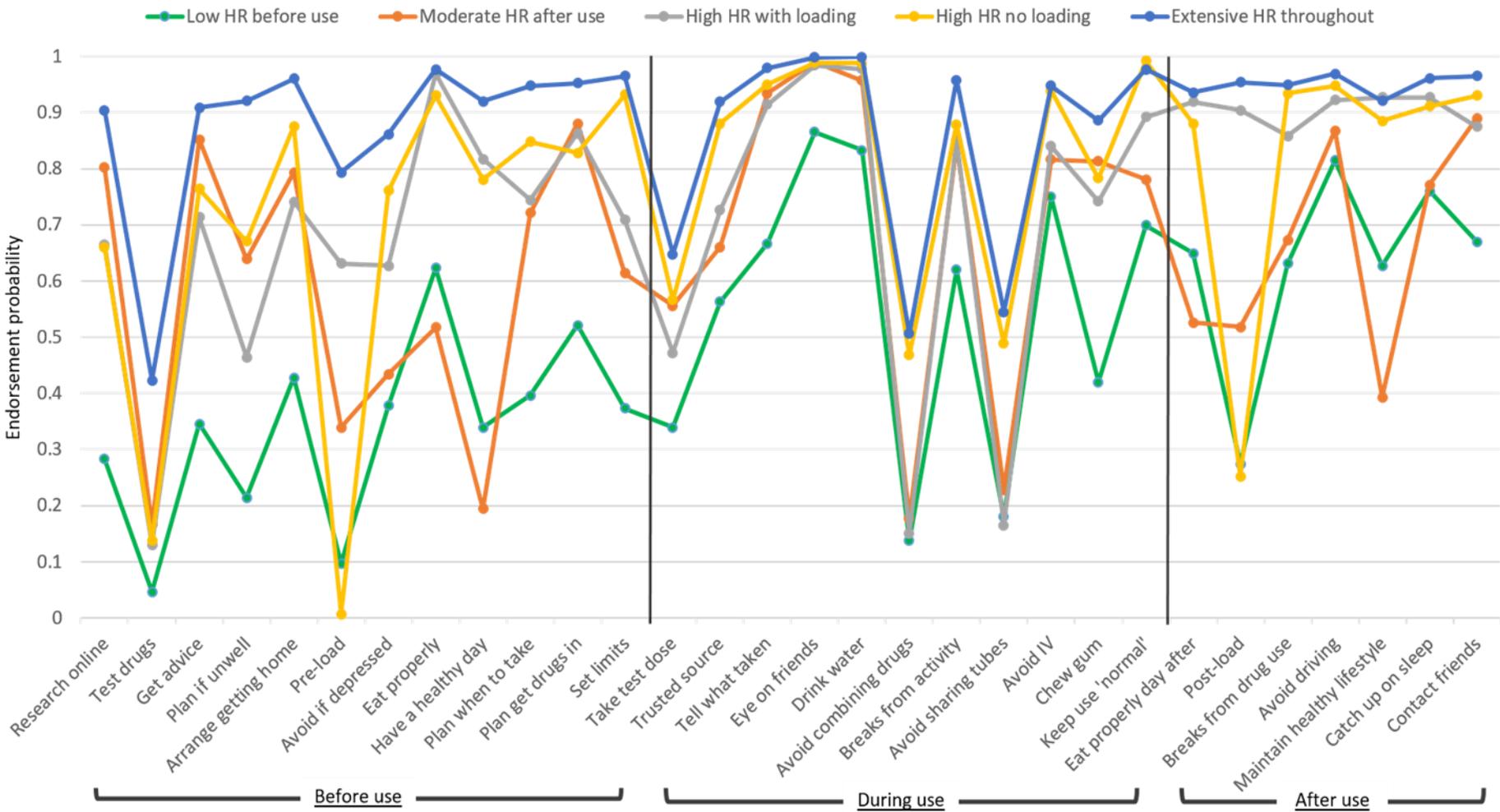


Table 4.5: Key defining characteristics of harm reduction classes

Class	Before use strategies	During use strategies	After use strategies
Low HR before use	<p>Low probabilities for the majority of strategies</p> <p>Moderate probabilities:</p> <ul style="list-style-type: none"> • Eat well before use • Plan how to get drugs in venue 	<p>Moderate probabilities for the majority of strategies</p> <p>High probabilities for:</p> <ul style="list-style-type: none"> • Keep an eye of friends • Drink safe amount of water • Avoid IV use <p>Low probabilities for:</p> <ul style="list-style-type: none"> • Avoid combining drugs and/or alcohol • Avoid sharing snorting paraphernalia 	<p>Moderate probabilities for the majority of strategies</p> <p>High probabilities for:</p> <ul style="list-style-type: none"> • Avoid driving under influence • Catch up on sleep <p>Low probability for:</p> <ul style="list-style-type: none"> • Take post-loading substances
	Moderate HR after use	<p>High probabilities for:</p> <ul style="list-style-type: none"> • Research new drugs online • Get advice from prior user • Arrange how to get home • Plan when to take drugs • Plan how to get drugs in venue <p>Moderate/low probabilities for:</p> <ul style="list-style-type: none"> • Avoid use when anxious/depressed • Eat properly • Have a healthy day • Take pre-loading substances 	<p>High probabilities for the majority of strategies</p> <p>Moderate probabilities for:</p> <ul style="list-style-type: none"> • Take test dose <p>Low probabilities for:</p> <ul style="list-style-type: none"> • Avoid combining drugs and/or alcohol • Avoid sharing snorting paraphernalia

Class	Before use strategies	During use strategies	After use strategies
High HR with loading	Moderate to high probabilities for the majority of strategies	High probabilities for the majority of strategies	
	Low probability for: <ul style="list-style-type: none"> • Drug testing 	Moderate probability for: <ul style="list-style-type: none"> • Take test dose Low probabilities for: <ul style="list-style-type: none"> • Avoid combining drugs and/or alcohol • Avoid sharing snorting paraphernalia 	High probabilities for all strategies
High HR no loading	Moderate to high probabilities for the majority of strategies	High probabilities for the majority of strategies	High probabilities for the majority of strategies
	Low probabilities for: <ul style="list-style-type: none"> • Drug testing • Take pre-loading substances 	Moderate probabilities for: <ul style="list-style-type: none"> • Take test dose • Avoid combining drugs and/or alcohol • Avoid sharing snorting paraphernalia 	Low probability for: <ul style="list-style-type: none"> • Take post-loading substances
Extensive HR throughout	High probabilities for the majority of strategies	High probabilities for the majority of strategies	
	Moderate probability for: <ul style="list-style-type: none"> • Drug testing 	Moderate probabilities for: <ul style="list-style-type: none"> • Take test dose • Avoid combining drugs and/or alcohol • Avoid sharing snorting paraphernalia 	High probabilities for all strategies

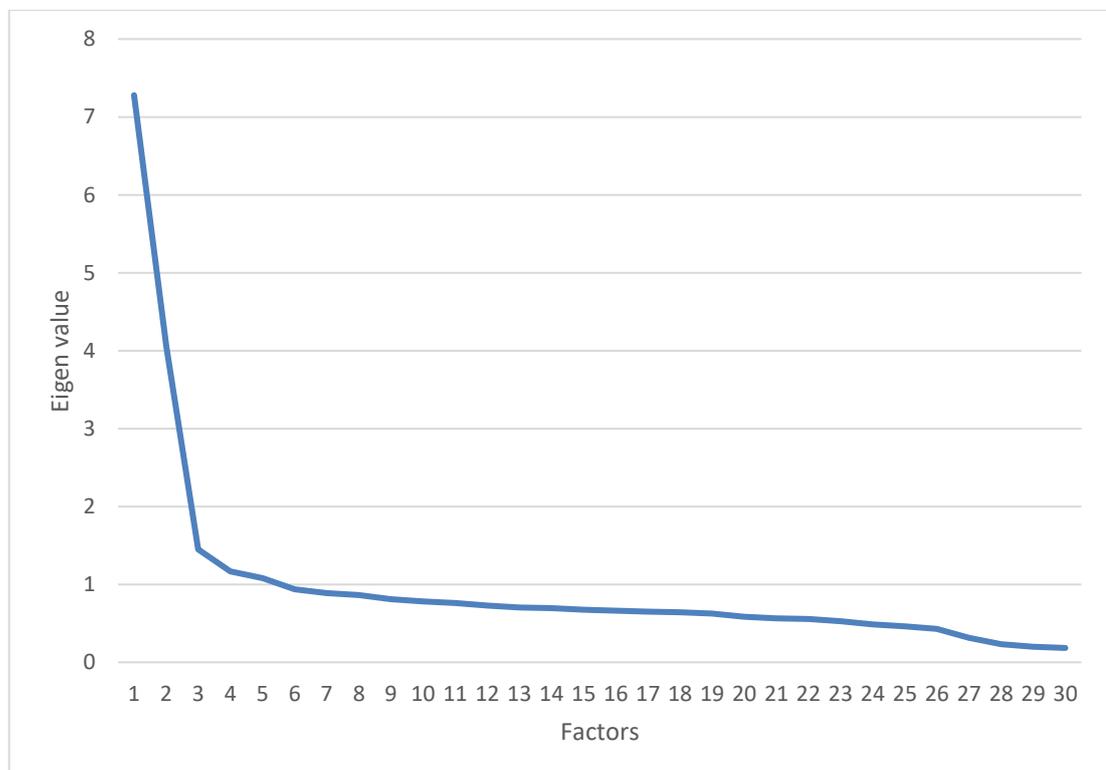
HR – Harm Reduction; IV - Intravenous

4. *High HR no loading* (23.47%): Very similar probability profile as the *High HR with loading* class, except with much lower probabilities for taking pre- or post-loading substances before or after drug use. Additionally, moderate rather than low probabilities were observed for avoiding combining drugs and avoiding sharing snorting paraphernalia.
5. *Extensive HR throughout* (29.91%): Very high probabilities of endorsing almost all of the harm reduction strategies. Testing drugs, taking a test dose, avoiding combining drugs and avoiding sharing snorting paraphernalia all had moderate endorsement probabilities.

4.3.3 Exploratory factor analysis of drug use experiences

Models postulating two, three, four and five factors had initial eigenvalues greater than 1, thus these solutions were examined using Geomin rotated loadings. The two factor solution was preferred because: the levelling off of eigenvalues on the scree plot after two factors (Figure 4.4); the poor number of loadings on the third and subsequent factors; and the theoretical support for two factors with additional factors not representing distinct subgroupings of experiences.

Figure 4.4: Negative consequence and positive experience factor analysis scree plot



As can be seen from the factor loadings displayed in Table 4.6, two items (“Driven/been driven by someone under the influence of alcohol or drugs” and “Legal problems e.g. being arrested”) did not have primary loadings of greater than 0.400 and so were removed. The two factors showed good discriminant validity, with no cross loadings greater than 0.300, and were labelled “positive experiences” (Factor 1) and “negative consequences” (Factor 2). Cronbach alphas for both factors were high (positive $\alpha=0.928$; negative $\alpha=0.846$) and composite scores were created for these two experience subscales.

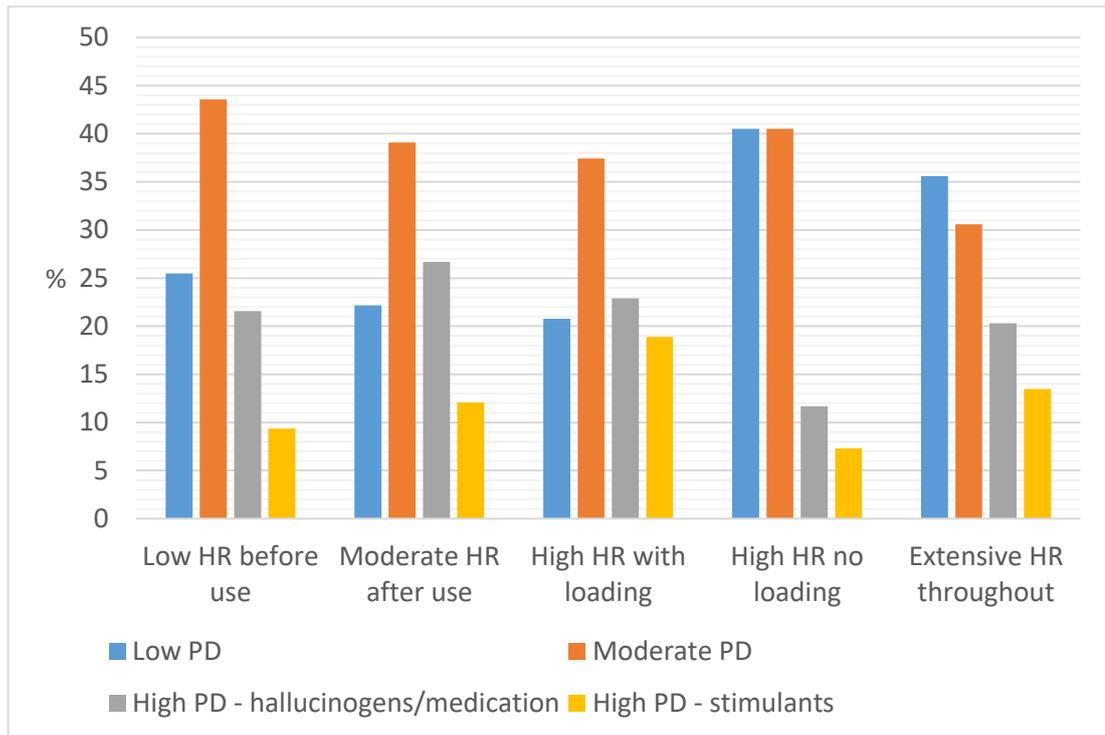
Table 4.6: Geomin rotated loadings for two factor solution

Item	Factor 1	Factor 2
Intense pleasure	0.844	-0.050
Enhanced perception and increased enjoyment of music	0.854	-0.027
Reduced inhibitions	0.676	0.077
Feelings of love and empathy	0.876	-0.013
Expanded consciousness	0.743	0.002
Increased sense of enlightenment	0.719	0.034
Closeness to others	0.852	0.008
Making new friends	0.700	0.067
Memory loss	0.271	0.404
Vomiting	0.054	0.454
Agitation	0.121	0.466
Accidents	-0.015	0.572
Aggression/victim of aggression	-0.062	0.559
Breathing difficulties	-0.031	0.558
Panic attacks/anxiety	-0.007	0.571
Arguments with friends	-0.050	0.541
Overheating	0.151	0.439
Fainting/collapsing	-0.066	0.445
Inability to move	-0.022	0.449
Sexual activity you later regret	-0.002	0.435
Driven/been driven by someone under the influence	0.067	0.301
Palpitations	0.071	0.474
Low mood/anxiety in days after use	0.254	0.446
Problems with a bouncer (e.g. drugs confiscated)	0.005	0.403
Legal problems (e.g. being arrested)	-0.025	0.296
Seeking/receiving emergency medical treatment	-0.061	0.433
Spending money you cannot afford to	0.075	0.486
Effect of the drug not as expected	0.063	0.457
Problems with sleep in days after use	0.152	0.458
Missing work or other important commitments	0.036	0.488

4.3.4 Harm reduction and polydrug use

Harm reduction classes significantly differed with respect to their levels of polydrug use, as defined by membership to one of the four polydrug using classes elicited in Chapter 3 (Figure 4.5). The most notable difference between the harm reduction classes was that the *High HR no loading* class had the highest proportion of low and moderate polydrug users, while the highest proportion of members in either of the two High polydrug using groups was observed in the *High HR with loading* class. A pairwise comparison between the *High HR no loading* and *High HR with loading* classes indicated that this difference was statistically significant ($\chi^2=140.22$, $p<0.001$). The class with the second highest proportion of High polydrug users was the *Moderate HR after use*, which also contained the highest percentage of members of the High – hallucinogens/medication polydrug class.

Figure 4.5: Percentage of polydrug use group within each harm reduction class



4.3.5 Discriminant validity of harm reduction classes

The five class latent class solution demonstrated good discriminant validity, in that omnibus tests showed that classes differed significantly on all demographic traits (see Table 4.1).

The *High HR with loading* and *Extensive HR throughout* classes contained the highest proportions of participants living in the UK or Netherlands, while the *Low HR before use* class had the highest proportions of individuals resident in the other three participating countries. The *Moderate HR after use* class had the lowest mean age, while the highest was observed in both the *Low HR before use* and *High HR with loading* classes being almost two years older on average. A higher proportion of women was seen in classes defined by higher probabilities of endorsing harm reduction strategies, such that the *Extensive HR throughout* class had the highest and the *Low HR before use* the lowest. Similarly, a pattern between levels of harm reduction and the number of events attended in the past 12 months was also observed, in that classes more likely to endorse use of harm reduction strategies attended on average fewer events in the past 12 months.

4.3.6 Associations between harm reduction class and positive and negative drug use experiences

4.3.6.1 Negative

The results from the linear regression of harm reduction class on the negative consequence subscale, adjusting for polydrug use, age, gender, country of residence, number of events attended in the past 12 months and highest levels of education are shown in Table 4.7.

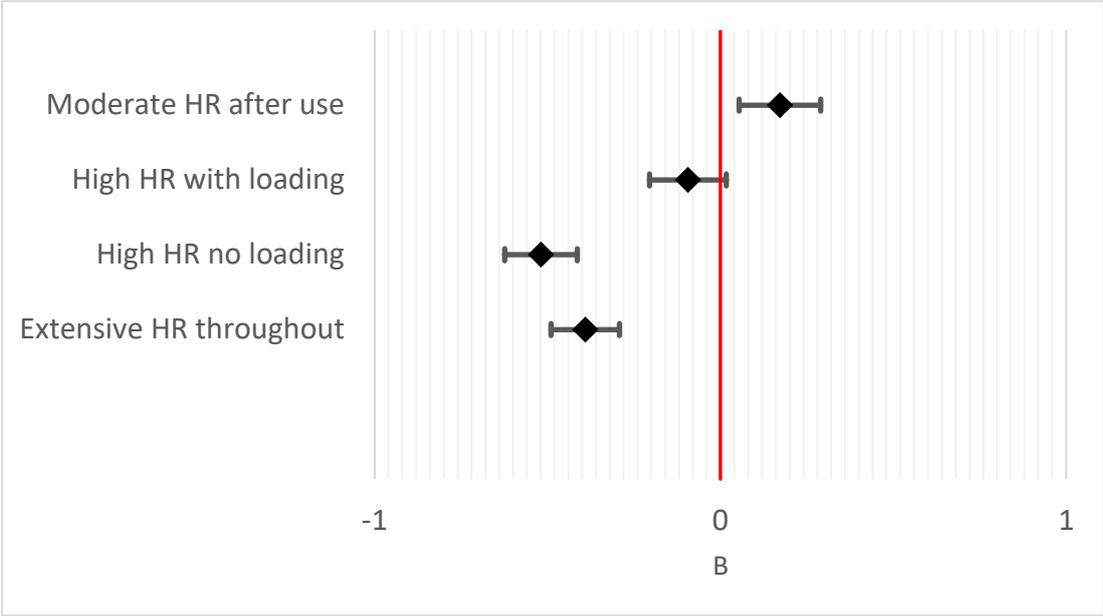
The plot of these adjusted regression coefficients for harm reduction classes are displayed in Figure 4.6. In comparison to the *Low HR before use* class, three out of four harm reduction classes significantly differed with respect to their mean score on the negative consequences subscale. Membership of the *High HR no loading* and *Extensive HR throughout* classes was associated with significantly lower scores, with the *High HR no loading* class having the largest difference, in comparison to the *Low HR before use* class. Conversely, the *Moderate HR after use* class was associated with significantly higher scores on the negative experience subscale than the *Low HR before use* class. Although the *High HR with loading* class had a lower mean negative experience subscale score than the *Low HR before use* class, this difference fell short of statistical significance.

Table 4.7: Results from linear regressions of negative consequences, adjusting for polydrug use and demographic characteristics

	B	95% CI	Beta	p
Harm reduction class				
Low HR before use	Reference			
Moderate HR after use	0.172	0.054, 0.290	0.060	0.004
High HR with loading	-0.094	-0.205, 0.018	-0.033	0.10
High HR no loading	-0.519	-0.624, -0.414	-0.208	<0.001
Extensive HR throughout	-0.391	-0.490, -0.291	-0.178	<0.001
Polydrug use class				
High PD – stimulants	0.212	0.127, 0.298	0.082	<0.001
High PD – hallucinogens / meds	0.233	0.160, 0.307	0.108	<0.001
Moderate PD	0.167	0.104, 0.230	0.094	<0.001
Low PD	Reference			
Gender				
Female	Reference			
Male	-0.205	-0.257, -0.152	-0.112	<0.001
Other	-0.184	-0.488, 0.121	-0.017	0.24
Country of residence				
Belgium	-0.155	-0.245, -0.066	-0.054	0.001
Italy	0.038	-0.093, 0.169	0.009	0.57
Netherlands	-0.381	-0.447, -0.315	-0.215	<0.001
Sweden	-0.356	-0.451, -0.262	-0.137	<0.001
UK	Reference			
Education				
Primary school / key stage 1 and 2	0.216	-0.027, 0.458	0.026	0.08
Secondary school / key stage 3	0.120	0.017, 0.223	0.043	0.02
GCSE / A-level / key stage 4	0.105	0.044, 0.167	0.061	0.001
University degree / NVQ4 or higher	Reference			
Age	-0.010	-0.017, -0.003	-0.050	0.004
Number of events	<0.001	-0.001, 0.001	0.000	0.99

B – unstandardized regression coefficient; Beta – standardized regression coefficient; 95% CI – 95% confidence interval. Abbreviations: PD – polydrug use; Px meds – prescription medication; UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification

Figure 4.6: Negative consequence regression coefficients and 95% confidence intervals, with Low HR before use class as reference



4.3.6.2 Positive

Table 4.8 displays the results of the linear regression of harm reduction class on the positive experience subscale, adjusting for polydrug use and demographic traits.

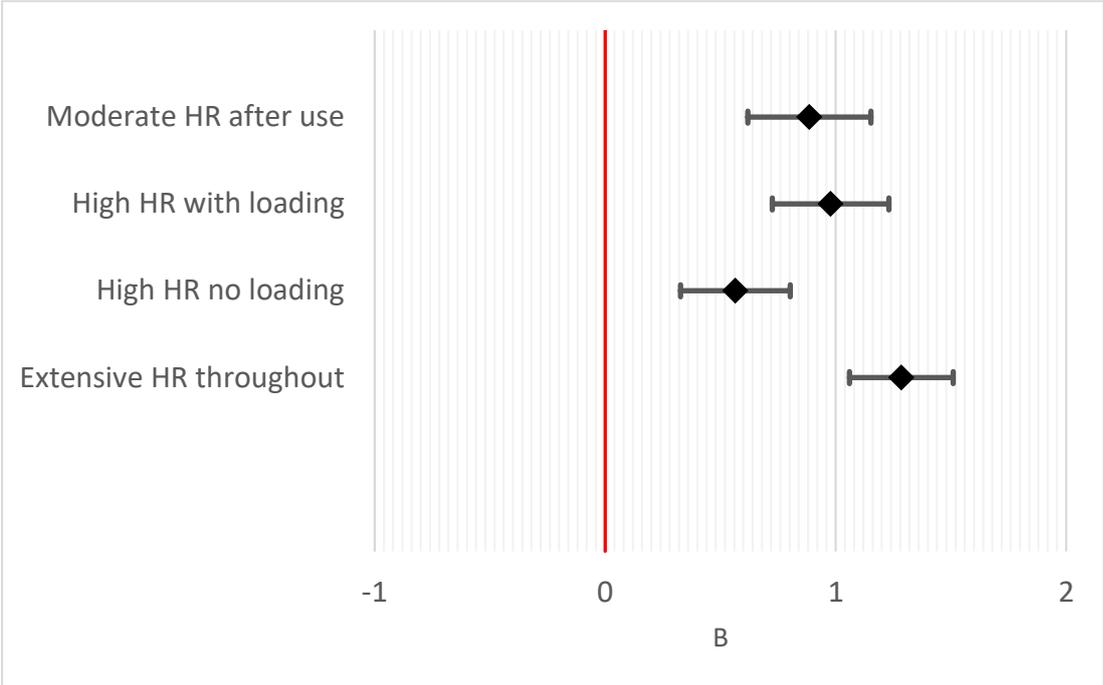
Adjusted regression coefficients are plotted in Figure 4.7, and show that in comparison to the *Low HR before use* class, all harm reduction classes were associated with significantly higher mean scores on the positive experiences subscale. Membership of the *Extensive HR throughout* was associated with the highest relative score, whereas the *High HR no loading* class was associated with the smallest difference when compared to the *Extensive HR throughout* class.

Table 4.8: Results from linear regression of positive experiences, adjusting for polydrug use and demographic characteristics

	B	95% CI	Beta	p
Harm reduction class				
Low HR before use	Reference			
Moderate HR after use	0.886	0.619, 1.154	0.142	<0.001
High HR with loading	0.978	0.725, 1.230	0.160	<0.001
High HR no loading	0.565	0.327, 0.804	0.104	<0.001
Extensive HR throughout	1.285	1.060, 1.510	0.269	<0.001
Polydrug use class				
High – stimulants	0.127	-0.068, 0.322	0.022	<0.001
High – hallucinogens / medication	0.247	0.080, 0.414	0.053	<0.001
Moderate	-0.067	-0.209, 0.076	-0.017	<0.001
Low	Reference			
Gender				
Female	Reference			
Male	-0.118	-0.237, 0.001	-0.030	<0.001
Other	-0.689	-1.380, 0.002	-0.029	0.24
Country of residence				
Belgium	0.050	-0.153, 0.253	0.008	0.63
Italy	-0.048	-0.346, 0.250	-0.005	0.75
Netherlands	0.060	-0.089, 0.209	0.016	0.43
Sweden	-0.917	-1.132, -0.702	-0.162	<0.001
UK	Reference			
Education				
Primary school / key stage 1 and 2	-0.361	-0.911, 0.189	-0.020	0.20
Secondary school / key stage 3	0.223	-0.011, 0.457	0.037	0.06
GCSE / A-level / key stage 4	0.094	-0.045, 0.234	0.025	0.19
University degree / NVQ4 or higher	Reference			
Age	0.014	-0.002, 0.030	0.032	0.004
Number of events	-0.002	-0.045, 0.234	-0.018	0.26

B – unstandardized regression coefficient; Beta – standardized regression coefficient; 95% CI – 95% confidence interval. Abbreviations: PD – polydrug use; Px meds – prescription medication; UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification

Figure 4.7: Positive experience regression coefficients and 95% confidence intervals, with Low HR before use class as reference



4.3.7 Associations between polydrug use and positive and negative drug use experiences

The mean frequency scores for each positive experience and negative consequences are displayed in Table 4.9. Overall, positive experiences had higher mean frequency scores than negative consequences. Polydrug use classes differed significantly on six of eight positive experience and nineteen of 22 negative consequence mean scores. With regard to positive experiences, the highest mean scores tended to be observed in one of the two *High polydrug use* classes. A less discernible pattern was observed with mean negative consequence frequency scores, although the lowest scores were found for the *Low polydrug use* for the majority. However, even significant differences between classes for both positive experiences and negative consequences appear small when considering that each item was measured on a scale from 0 to 10.

Table 4.9: Mean positive experience and negative consequence frequency scores by polydrug use class

	Low PD use	Moderate PD use	High PD use – hallucinogens /meds.	High PD use – stimulants	F	p
	Mean (95% CI)	Mean (95% CI)	Mean (95% CI)	Mean (95% CI)		
Positive experiences						
Intense pleasure	8.02 (7.89, 8.14)	7.59 (7.48, 7.71)	7.96 (7.83, 8.10)	8.54 (8.41, 8.68)	26.42	<0.001
Enhanced perception and increased enjoyment of music	8.23 (8.11, 8.34)	8.00 (7.89, 8.10)	8.34 (8.21, 8.46)	8.45 (8.31, 8.59)	8.75	<0.001
Reduced inhibitions	6.38 (6.22, 6.55)	6.46 (6.32, 6.60)	6.59 (6.40, 6.78)	7.32 (7.12, 7.52)	14.57	<0.001
Feelings of love and empathy	7.39 (7.25, 7.53)	7.28 (7.16, 7.40)	7.19 (7.03, 7.36)	7.18 (6.98, 7.38)	1.56	0.197
Expanded consciousness	5.74 (5.56, 5.91)	5.38 (5.23, 5.53)	6.43 (6.23, 6.62)	6.12 (5.88, 6.35)	23.92	<0.001
Increased sense of enlightenment	5.56 (5.39, 5.73)	5.15 (4.99, 5.31)	5.80 (5.60, 6.01)	5.88 (5.63, 6.13)	11.51	<0.001
Closeness to others	6.78 (6.63, 6.93)	6.70 (6.57, 6.84)	6.97 (6.80, 7.14)	6.60 (6.38, 6.81)	2.49	0.058
Making new friends	5.93 (5.77, 6.10)	6.12 (5.97, 6.27)	6.48 (6.30, 6.67)	6.39 (6.15, 6.62)	7.14	<0.001
Negative consequences						
Memory loss	2.49 (2.34, 2.64)	3.16 (3.01, 3.30)	3.35 (3.16, 3.55)	2.97 (2.74, 3.20)	19.17	<0.001
Vomiting	0.85 (0.75, 0.95)	1.24 (1.14, 1.34)	1.38 (1.25, 1.52)	1.12 (0.95, 1.30)	15.12	<0.001
Agitation	1.23 (1.11, 1.34)	1.85 (1.74, 1.97)	1.94 (1.79, 2.09)	1.47 (1.29, 1.64)	26.18	<0.001
Accidents	0.30 (0.25, 0.35)	0.44 (0.38, 0.49)	0.66 (0.57, 0.75)	0.33 (0.25, 0.40)	20.57	<0.001
Aggression/victim of aggression	0.24 (0.19, 0.29)	0.43 (0.37, 0.48)	0.45 (0.37, 0.53)	0.19 (0.13, 0.25)	14.93	<0.001
Breathing difficulties	0.38 (0.32, 0.45)	0.54 (0.47, 0.61)	0.53 (0.45, 0.62)	0.49 (0.38, 0.60)	3.99	0.008
Panic attacks/anxiety	0.82 (0.73, 0.92)	1.16 (1.07, 1.26)	1.07 (0.94, 1.20)	0.79 (0.65, 0.94)	10.51	<0.001
Arguments with friends	0.30 (0.24, 0.35)	0.40 (0.35, 0.45)	0.48 (0.40, 0.56)	0.24 (0.17, 0.32)	7.67	<0.001
Overheating	1.21 (1.09, 1.32)	1.46 (1.35, 1.57)	1.50 (1.35, 1.64)	1.01 (0.85, 1.16)	9.19	<0.001
Fainting/collapsing	0.15 (0.11, 0.20)	0.14 (0.11, 0.18)	0.19 (0.14, 0.25)	0.14 (0.08, 0.19)	0.81	0.488
Inability to move	0.20 (0.16, 0.25)	0.37 (0.31, 0.42)	0.53 (0.44, 0.62)	0.32 (0.24, 0.40)	15.55	<0.001
Sexual activity you later regret	0.33 (0.26, 0.40)	0.54 (0.47, 0.61)	0.54 (0.45, 0.64)	0.30 (0.22, 0.39)	9.44	<0.001

	Low PD use	Moderate PD use	High PD use – hallucinogens /meds.	High PD use – stimulants	F	p
	Mean (95% CI)	Mean (95% CI)	Mean (95% CI)	Mean (95% CI)		
Driven/been driven by someone under the influence	0.62 (0.53, 0.70)	0.93 (0.84, 1.02)	1.19 (1.04, 1.33)	1.08 (0.90, 1.26)	17.83	<0.001
Palpitations	0.37 (0.31, 0.43)	0.66 (0.58, 0.74)	0.96 (0.84, 1.08)	0.71 (0.58, 0.84)	26.89	<0.001
Low mood/anxiety in days after use	0.90 (0.80, 0.99)	1.22 (1.12, 1.32)	1.25 (1.11, 1.39)	1.62 (1.44, 1.80)	18.07	<0.001
Problems with a bouncer (e.g. drugs confiscated)	2.33 (2.18, 2.48)	3.32 (3.17, 3.46)	3.09 (2.91, 3.28)	2.63 (2.41, 2.84)	33.20	<0.001
Legal problems (e.g. being arrested)	0.21 (0.17, 0.25)	0.38 (0.33, 0.44)	0.53 (0.44, 0.62)	0.24 (0.18, 0.31)	18.49	<0.001
Seeking/receiving emergency medical treatment	0.11 (0.07, 0.15)	0.15 (0.11, 0.19)	0.22 (0.15, 0.29)	0.06 (0.03, 0.09)	5.17	0.001
Spending money you cannot afford to	0.10 (0.07, 0.14)	0.14 (0.10, 0.18)	0.15 (0.10, 0.19)	0.15 (0.09, 0.21)	0.78	0.504
Effect of the drug not as expected	0.66 (0.57, 0.75)	1.70 (1.57, 1.82)	1.82 (1.64, 1.99)	1.03 (0.86, 1.20)	70.15	<0.001
Problems with sleep in days after use	0.88 (0.79, 0.97)	1.05 (0.96, 1.14)	1.34 (1.22, 1.47)	1.10 (0.96, 1.24)	12.48	<0.001
Missing work or other important commitments	1.41 (1.29, 1.53)	1.90 (1.77, 2.02)	2.09 (1.92, 2.27)	2.11 (1.90, 2.32)	19.04	<0.001
Bonferroni corrected significant differences (0.05 / 30 = 0.0017) highlighted in bold						

4.4 Discussion

This study examined the adoption of an extensive range of harm reduction strategies amongst polysubstance using nightlife attendees in Europe, and their association with positive experiences and negative consequences. Consistent with previous research (Akram & Galt, 1999; Allott & Redman, 2006; Davis & Rosenberg, 2017; F. Fernández-Calderón et al., 2014; Fernández-Calderón et al., 2019; Vera et al., 2018), the use of harm reduction strategies was widely endorsed. That over 50% of our sample reported that they employed 26 of the 30 strategies in the past 12 months further lends support to suggestions that polydrug using nightlife attendees are aware of the risk of harm their drug use poses, and employ a range of protective behavioural strategies to mitigate these risks (F. Fernández-Calderón et al., 2014; Fernández-Calderón et al., 2019).

In the first investigation into harm reduction profiles using LCA of which the author is aware, five distinct classes were identified characterised by their differing probabilities of endorsing 30 protective behavioural strategies in the past 12 months. Identified classes were labelled as follows: *Low HR before use* (comprising 10.94% of the sample); *Moderate HR after use* (15.37%); *High HR with loading* (20.31%); *High HR no loading* (23.47%); *Extensive HR throughout* (29.91%). That the discriminant validity of this five class solution was confirmed provides the first evidence for heterogeneous profiles of harm reduction amongst polydrug users in those regularly engaging with European nightlife. Furthermore, the adoption of a more comprehensive range of harm reduction strategies was associated with lower negative consequence and higher positive experience subscale scores, while profiles also differed with respect to their levels of polydrug use. These findings are discussed in further detail below.

4.4.1 Description of harm reduction profiles

Inspection of the probability plot (Figure 4.3) shows that the five harm reduction classes predominantly differed with regard to strategies employed before and after drug use. Differences between classes during use were less pronounced and tended to follow an additive pattern, as evidenced by the close proximity and minimal crossing of the plot lines for these eleven strategies. However, there is greater distance between, and more overlap of, plot lines for before and after strategies, suggesting differences between classes for these are more nuanced. These differing patterns therefore show the importance of considering harm reduction in a wider context, and building on previous findings (e.g.

Fernández-Calderón et al., 2019) to include strategies beyond those just employed during use. Findings presented here suggest that targeted harm reduction strategies may be most able to change behaviours when focusing on those before and after use.

4.4.1.1 Extensive HR throughout

Members of the *Extensive HR throughout* class had high probabilities (>0.70) of endorsing all but three of the 30 strategies, with moderate probabilities for testing drugs using a home test kit or testing service (0.42), avoiding combining illicit drugs and/or alcohol (0.50), and avoid sharing tubes or notes when snorting drugs (0.54).

4.4.1.1.1 Drug testing

Despite only a moderate probability for testing drugs before using them, the *Extensive HR throughout* class in fact had the highest probability with the four remaining classes all having very low probabilities of employing this strategy. This is consistent with a study of Spanish ravers, which found that the majority (79.9%) of participants reported never or almost never testing their drugs in the past 12 months (F. Fernández-Calderón et al., 2014), and taken together may suggest that this strategy is not commonly adopted in European nightlife populations.

One potential explanation for the low probabilities of drug testing is the limited availability of these facilities in the countries in our sample. Indeed, at the time of data collection, the only nationwide system of testing facilities existed in the Netherlands (Drug Information and Monitoring System; DIMS), with small scale government funded facilities in Belgium and Wales in the UK (Brunt, 2017). However, almost two thirds of participants living in the Netherlands (64.61%) belonged to one of the four classes characterised by very low probabilities of drug testing. This indicates that decisions to adopt this strategy are based upon more than just service availability. Given concerns about the rising strength of drugs and the use of potentially more dangerous substances as adulterants, promoting the use of drug testing services where available may be a sensible approach. A pilot study of a drug testing service provided at a UK festival in 2016 revealed that 20% of the 230 samples submitted for analysis were not as sold, instead containing cheaper psychoactive substances, pharmaceuticals and cutting agents or inactive substances such as plaster of paris (Measham, 2019). Furthermore, two-thirds of participants whose drugs were not as sold decided to discard their sample, suggesting that the results from drug testing services can influence drug taking behaviours. Similar results have been observed in the USA, with

participants approximately half as likely to report using a sample bought as MDMA if test results showed it contained a different substance (Relative Risk = 0.56; Saleemi, Pennybaker, Wooldridge, & Johnson, 2017). While further research into the influence of drug testing on use intentions and the mitigation of risks is required, that there is preliminary evidence that drug users modify their intentions to use based upon knowledge of what drugs contain suggests utilising testing services where available should be promoted, particularly in light of concerns about high potency and adulterated drugs on the European market.

4.4.1.1.2 Avoiding combined use of different illicit drugs and/or alcohol

The fact that avoiding combining illicit drugs and/or alcohol was only endorsed with moderate probability by the *Extensive HR throughout* class is not surprising given this is a sample identified as polydrug users, and is in line with findings from previous research (F. Fernández-Calderón et al., 2014). The *High HR no loading* class also had a similarly moderate probability of endorsing this strategy (0.47), while probabilities for the remaining three classes were low (<0.18 for all), suggesting that polydrug use may occur in different contexts for different people. Specifically, it may be that for a number of people in the *Extensive HR throughout* and *High HR no loading* classes who avoid combining substances, polydrug use occurs via use of different substances on different occasions over a given time, while concomitant drug use is more common amongst members of the remaining three classes. As discussed in Chapter 3, use of multiple substances at the same time is thought to increase the risk of drug related harm due to unknown temporal interactions, and these findings suggest young adults in the European nightlife scene may benefit from efforts aimed to increase awareness of these risks.

4.4.1.1.3 Avoiding sharing snorting paraphernalia

Probabilities of avoiding sharing snorting paraphernalia followed a similar pattern, in that they were moderate in both the *Extensive HR throughout* and *High HR no loading* (0.49) classes and less than 0.22 in the remaining three. The only previous study to specifically look at this strategy amongst polydrug users similarly found that this was not universally adopted, with 37.7% responding that they never or almost never avoid sharing tubes (F. Fernández-Calderón et al., 2014). This highlights another behaviour that should be promoted, given the risk of transmission of blood born viruses such as hepatitis carried by

sharing, for example, bank notes or straws when snorting drugs (Aaron et al., 2008; Scheinmann et al., 2007).

4.4.1.2 High HR with loading and High HR no loading

Two further classes that had high probabilities of endorsing the majority of strategies were identified (*High HR with loading* and *High HR no loading*), with lower probabilities for behaviours employed before use primarily distinguishing them from the *Extensive HR throughout* class. While these two classes displayed similar harm reduction profiles in that their probability plots were in close proximity across most strategies (see Figure 4.3), there was one key difference beyond avoid combining drugs and sharing snorting paraphernalia discussed above.

This defining characteristic was that the *High HR with loading* class endorsed pre-loading with moderate probability (0.63) and post-loading with high probability (0.90), while the *High HR no loading* had very low to low probabilities for these two strategies (pre-loading: 0.007; post-loading: 0.25). Taking pre- and post-loading substances has typically been explored as a protective behaviour specifically against ecstasy related neurotoxicity (Allott & Redman, 2006; Kelly, 2009), thus it may be that members of the *High HR no loading* class were less likely to have used ecstasy in the past 12 month, and as a consequence less likely to post-load. However, all polydrug use classes identified Chapter 3 that form the sample for this study had similarly high probabilities of endorsing past 12 month ecstasy use, thus this cannot be the explanation for differences in pre- and post-loading between harm reduction classes. Given that no study examining associations between harm reduction and negative drug use experiences has investigated pre- or post-loading (Fernández-Calderón et al., 2019; Vera et al., 2018; Vidal Gine et al., 2016), further research is required in order to inform decisions about whether these strategies should be promoted.

4.4.1.3 Low HR before use and Moderate HR after use

The most moderate harm reduction profiles were exhibited by the *Low HR before use* and *Moderate HR after use* classes, and were also the smallest in terms of sample size. The largest differences between these two classes were found in probabilities of endorsing strategies before use. The *Moderate HR after use* class had similar probabilities to the three high harm reduction groups for strategies before use that relate to researching and planning drug use. These include researching new drugs online, getting advice from a prior user, setting limits on the amounts used and planning what to do if someone becomes

unwell and how to get home. However, far lower probabilities were observed for protective behaviours that could be conceptualised as relating to maintaining general health, such as eating properly and having a healthy day before use, and avoiding use when feeling anxious or depressed. The *Low HR before use* class had considerably lower probabilities of endorsing before use strategies than the three high use group. While probabilities for these strategies were also mostly lower than those for the *Moderate HR after use* group, they were in fact slightly higher for eating well and having a healthy day before going out, and comparable for avoiding use when depressed or anxious.

To date, the association between harm reduction behaviours employed before use and negative outcomes is limited to just two strategies. More frequent adoption of both setting limits on the amounts used and trying not to exceed them (Fernández-Calderón et al., 2019; Vera et al., 2018; Vidal Gine et al., 2016) and planning use sessions rather than taking what someone offers (Vera et al., 2018) has been modestly associated with a reduction in odds of experiencing negative consequences of drug use. However, results from this LCA suggest that polydrug users engaging with the European nightlife scene employ a wider range of strategies to prepare for drug use in differing patterns, and these should be considered in future research.

The *Low HR before use* and *Moderate HR after use* classes typically had lower probabilities of endorsing harm reduction strategies after use than the other three classes (except for the relatively low probability observed for post-loading in the *High HR no loading* class). In line with differences in patterns of adoption of before use strategies, the *Moderate HR after use* had lower probabilities of maintaining a healthy lifestyle with regard to sleep, exercise and diet than the *Low HR before use* class. Similarly, as with pre-loading, the *Moderate HR after use* group had higher probabilities of post-loading than the *Low HR before use* class. No study has included strategies that are adopted after use when examining relationships with negative outcomes, but LCA results from this study suggest they are differentially adopted amongst this population and should be included as part of a wider approach to harm reduction.

4.4.2 Harm reduction and polydrug use

Few studies have investigated the relationship between polydrug use and harm reduction strategies. A negative relationship has been detected in two studies whereby the use of an increasing number of drugs was associated with adoption of fewer harm reduction

strategies, in what has been described a 'cautious' profile (F. Fernández-Calderón et al., 2014). In a sample of ecstasy users living in Spain, increases in the mean number of other drugs used in the past 12 months was significantly associated with a lower probability of using small doses, spacing out sessions and avoiding mixing stimulants (Vera et al., 2018). Similarly, amongst a sample of ravers in Spain, low polydrug users (defined as use of four or fewer drugs in the past month) were found to employ eight of sixteen harm reduction strategies more frequently than those defined as high polydrug users (F. Fernández-Calderón et al., 2014).

Findings from a recent study into polydrug using festival attendees, however, indicate that this relationship may be more complex. Rather than dichotomising the sample into high and low polydrug users (F. Fernández-Calderón et al., 2014) or using the total number of drugs used in the past 12 months (Vera et al., 2018), Fernández-Calderón and colleagues (2019) examined how the past 12 month use of different substances were related to six 'dosing' related harm reduction strategies and found differing patterns of associations. For example, past 12 month stimulant users were found to be less likely to frequently adopt five out of six strategies, while ecstasy use was associated with increased odds of taking smaller rather than larger doses and avoid mixing depressants. Furthermore, those reporting use of new psychoactive substances in the past 12 months had a higher probability of frequently utilising four out of six strategies (Fernández-Calderón et al., 2019).

Given that the use of various substances may be related to harm reduction strategies in different ways, it is important to consider these associations beyond the total number of drugs consumed. Indeed, this echoes conclusions from Chapter 3 that polydrug use amongst young adults regularly engaging with the European nightlife scene is more nuanced than a purely additive concept. As such, one of the aims of this study was to examine the relationship between classes of harm reduction and polydrug use patterns detected in Chapter 3.

The identified harm reduction profiles differed significantly in terms of membership to the four polydrug use classes. The highest proportions of low polydrug users were found in the *High HR no loading* and *Extensive HR throughout* harm reduction classes, somewhat lending support to the notion of a 'cautious' profile of harm reduction and polydrug use (F. Fernández-Calderón et al., 2014; Vera et al., 2018). To fully support this, however, one would expect to find the largest proportions of high polydrug users in the harm reduction

class characterised by the lowest probabilities of strategy endorsement. While some evidence of this was found in that the *Moderate HR after use* had the second highest percentage of High – hallucinogens/medication or High – stimulants polydrug users (38.76%), the largest was found in the *High HR with loading* class (41.79%) then the *Extensive HR throughout* class (33.39%). Furthermore, the lowest was observed in the *High HR no loading* class (18.98%). It may be, therefore, that the *High HR no loading* class represents a profile that adopts the ‘cautious’ approach to polydrug use and harm reduction, while other profiles exist that do not follow this pattern.

The characteristic that distinguishes the *High HR no loading* class from the other high harm reduction classes is the far lower probabilities of adopting pre- and post-loading. Given that just over a third (33.39%) of members of the *Extensive HR throughout* harm reduction class were also high polydrug users, it may be that pre- and post-loading are behaviours that are particularly associated with increasing levels of polydrug use.

4.4.3 Harm reduction and demographic characteristics

The discriminant validity of identified harm reduction profiles was confirmed through statistically significant omnibus tests on demographic characteristics. Although some studies have found younger age to be associated with the adoption of harm reduction strategies (Fernández-Calderón et al., 2019; Vera et al., 2018), there was no discernible pattern of association between age and harm reduction profiles, with both the *Low HR before use* and *High HR with loading* classes having the highest mean age (24.76 years) and the *Moderate HR after use* the lowest (22.83 years).

A relationship between harm reduction and gender was evident, in that higher proportions of women were found in classes defined by higher probabilities of endorsing harm reduction strategies. This finding is consistent with previous research that has shown women are more likely to employ harm reduction behaviours related to alcohol (Benton et al., 2004), cannabis (Bravo, Prince, Pearson, et al., 2017), ecstasy (Vera et al., 2018) and polydrug use (Akram & Galt, 1999; Fernández-Calderón et al., 2019).

The mean number of events attended in past 12 months decreased as harm reduction increased as defined by latent class membership. To the author’s knowledge, only one study has examined this previously and found that more frequent attendance at raves in the past month was associated with a lower probability of avoiding or being careful about mixing stimulants, but no other strategy (F. Fernández-Calderón et al., 2014). Given the

association between more frequent event attendance and levels of drug use discussed in Chapter 3, the relationship between attendance and the adoption of harm reduction strategies warrants further investigation, as polydrug users who more frequently engage with the European nightlife scene may represent a particularly at risk group.

Country level differences were also observed. The lowest proportion of participants living in the UK was found in the class characterised by the lowest probabilities of strategy adoption, while the *High HR with loading* and *Extensive HR throughout* classes contained the highest percentages of those living in the Netherlands. These two countries were also identified as being the largest contributors to the High polydrug using classes in Chapter 3. Taken together, these findings suggest that while polydrug users in the UK and the Netherlands may be at elevated risk of harm, they employ a wide range of protective strategies to mitigate these risks.

4.4.4 Harm reduction and negative consequences of drug use

Harm reduction profiles differed in comparison to the *Low HR before use* class with respect to mean scores on the negative consequence subscale, after adjusting for polydrug use and demographic traits. Both the *High HR no loading* and *Extensive HR throughout* classes had significantly lower mean scores, while the lower score found for the *High HR with loading* class was not statistically significant. However, even significant differences with the *Low HR before use* class were very small, with the largest observed for the *High HR no loading* being just 0.52 points less on a scale of 0 to 10. Conversely, the *Moderate HR after use* class had a higher relative mean score in comparison to the *Low HR before use* class. Again this difference was very small, with the lower bound limit of the 95% confidence interval for the regression coefficient suggesting the mean could be as little as 0.05 points higher.

That two out of three classes characterised by high or extensive endorsement of harm reduction strategies were associated with lower scores on the negative consequence subscale than the *Low HR before use* class is somewhat consistent with previous research into polydrug users. Investigating the association between dosing related strategies and negative consequences, Fernández-Calderón et al (2019) found that all strategies, with the exception of taking smaller doses, were associated with lower odds of experiencing at least one of thirteen negative outcomes related to drug use. However, many of the confidence intervals approached the null value of 1, indicating that true differences may be very small. Similar findings have been observed amongst ecstasy (Vera et al., 2018) and ketamine

(Vidal Gine et al., 2016) users, in that four out of seven and four out of six strategies respectively were associated with lower odds of experiencing one or more negative consequence. Again, however, confidence intervals for a number of odds ratios in both studies were close to the null.

The finding that the *Moderate HR after use* class was associated with a significantly higher mean negative consequence subscale score than the *Low HR before use* class is not in line with Fernández-Calderón et al (2019), who did not find any positive associations between harm reduction strategies and negative consequences. This warrants further exploration, as it may be that harm reduction approaches are only beneficial when a wide range of strategies are adopted, particularly those related to maintaining general health. This further highlights the need to consider an extensive set of behavioural strategies when assessing how harm reduction is associated with negative outcomes of drug use.

Interestingly, compared to the *Low HR before class*, the *High HR no loading* class had the largest difference in mean negative consequence subscale scores, while that for the *High HR with loading* was not significantly different. As discussed, the key difference between these two classes is found in their respective probabilities for endorsing pre- and post-loading. However, the *Extensive HR throughout* class also had high probabilities of endorsing these strategies and significantly lower negative consequence subscale scores. It may be, therefore, that any benefit of pre- and post-loading depends upon the adoption of further strategies. No study looking at harm reduction strategies and negative outcomes has included pre- or post-loading, thus further research is required. Furthermore, given qualitative evidence that a variety of substances are consumed for different reasons (Kelly, 2009), an understanding of what is used when pre- and post-loading would be important in furthering the understanding of the relationship between these strategies and negative consequences of drug use.

These findings contribute to the evidence that discrete patterns of endorsement of harm reduction strategies differentially relate to negative consequences, with greater levels of use tending to result in fewer negative consequences. However, small regression coefficients suggest that differences may only be modest.

The fact that only small differences were detected may be due to floor effects of the negative consequences subscale. Indeed, the mean score for the sample as a whole was only 1.0, indicating that, on average, negative consequences were experienced with very

low frequency. This shows the importance of accounting for frequency when exploring associations with negative consequences amongst this population, rather than, for example, whether or not a consequence was experienced in the past 12 months as in previous research (Fernández-Calderón et al., 2019). As far as the author is aware, this is the first study to account for frequency of consequences when examining their relationship with harm reduction strategies. Although 20 negative experiences were used to create the subscale, it is possible that some consequences that may be experienced with more frequency were not captured. Alternatively, these results may suggest that negative consequences do not occur with great frequency amongst polydrug users in the European nightlife scene, possibly due to widespread adoption of harm reduction practices. Future research should incorporate measures of frequency and consider additional consequences to examine this further.

4.4.5 Harm reduction and positive experiences of drug use

This study provides the first empirical investigation into the associations between the adoption of harm reduction strategies and positive experiences of drug use. Compared to the *Low HR before use* class, all four classes that were defined by increased endorsement of harm reduction strategies had significantly higher scores on the positive experience subscale, after adjusting for polydrug use and demographics. The largest difference was observed in the *Extensive HR throughout* class, providing the first evidence that more widespread adoption of harm reduction strategies may be associated with more positive experiences from drug use. Furthermore, while this difference was modest at 1.3 points on a scale of 0 to 10, it was considerably larger than that observed for negative consequences.

As discussed, the largest differences between the *Low HR before use* class and the other four latent classes were observed in strategies employed before use. It could be, therefore, that the adoption of a range of strategies to prepare for drug use may lead to a more enjoyable experience. This supports findings from the 'High-way Code' in which a range of strategies before use, such as avoiding use when depressed, setting limits and planning sessions in advance were not universally adopted but a large proportion of those who did said they increased their enjoyment from using a drug (GDS, 2014). Interestingly, confidence intervals for the regression coefficient for the *Moderate HR after use* overlap with those for the three classes characterised by more wide spread adoption of harm reduction strategies. It may be, therefore, that employing strategies that are related to researching and planning use, such as researching new drugs online, getting advice from a

prior user and planning when to take drugs, leads to more enjoyable experiences. While the cross sectional design of this study precludes claims of causality, this is an important preliminary finding worthy of further exploration.

The *High HR no loading* class had the smallest difference in mean positive experience subscale scores when compared to the *Low HR before use* class. As a key feature of this class was the far lower probabilities observed for pre- and post-loading than all but the *Low HR before use* class, it may be that the adoption of these strategies in particular is associated with a more positive experience of drug use. Again, claims of a causal relationship cannot be made, but if a relationship exists it is likely to be between pre-loading and positive experiences, as items on the subscale concerned the acute subjective effects of a drug that would likely occur before post-loading.

This study contributes to existing but limited evidence that the use of harm reduction strategies amongst polydrug using nightlife attendees is associated with experiencing fewer negative experiences of drug use. This is also the first empirical finding that suggests profiles of harm reduction characterised by extensive adoption of strategies are associated with experiencing more positive subjective effects of use. Furthermore, the largest difference observed in mean subscale scores was substantially higher for positive experiences than for negative consequences. This is an important finding as research to date has focussed solely on the associations between harm reduction behaviours and negative consequences, and it seems logical to suggest that the promotion of strategies that both enhance the subjective pleasure of drug use and mitigate against harm would be well received by polydrug users. The importance of considering positive as well as negative experiences is also illustrated by the fact that the mean frequency scores for positive experiences were far higher than for negative consequences (Table 4.2). That the highest mean scores for positive experiences tended to be observed in one of the two *High polydrug use* classes underlines the importance of including positive experiences when designing and evaluating interventions targeting those potentially most at risk of drug related harm. Although fewer in number than by polydrug use class, where significant differences by gender were observed they tended to be that females experienced both positive experiences and negative consequences more frequently than males, suggesting females may be particularly receptive to the promotion of strategies designed to both increase enjoyment and mitigate the risk of drug related harm.

Future research should, therefore, include positive experiences as well as negative consequences when examining associations with harm reduction strategies. Furthermore, additional experiences should be included in future studies with longitudinal designs to further elucidate which strategies may protect against harm and thus should be widely promoted amongst populations regularly engaging with European nightlife.

4.4.6 Strengths and limitations

One major strength of this study is that it is the first to use LCA to identify discrete harm reduction profiles, characterised by differing probabilities of endorsing an extensive range of personal behavioural strategies in the past 12 months. The confirmation of the discriminant validity of the chosen solution highlights the utility of this method in identifying patterns of harm reduction behaviours in a European nightlife population. The inclusion of a far wider range of strategies than previous studies is also a strength, as evidenced by important differences between classes emerging for strategies employed before, during and after drug use. Furthermore, using polydrug using classes identified in Chapter 3 enabled the exploration of the relationship between harm reduction strategies and more nuanced patterns of drug use than simply an additive model.

A further strength of this particular study is the use of factor analysis to create subscales of negative consequences and positive experiences with high internal reliability. This is also the first study to consider how harm reduction strategies relate to positive experiences of drug use, which might be vital for the successful promotion of behaviours that reduce the risk of harm. Additionally, this study accounted for the frequency of consequences and experiences, rather than simply whether or not something occurred, for example, in the past 12 months (Fernández-Calderón et al., 2019).

Despite a number of strengths to this study, limitations do need to be considered. For reasons of brevity, the EMSS did not ask about how frequently harm reduction strategies were employed, rather just whether or not they were adopted in the past 12 months. Given that the harm reduction strategies were widely adopted, information on frequency would have allowed the dichotomising of the sample into high and low frequency groups which may have uncovered more nuanced profiles of use. Furthermore, an assessment of how frequently harm reduction strategies were employed might have enabled the use of more complex latent indicator variables that may have elicited more fine grained and potentially informative harm reduction profiles. In order to address this limitation, future iterations of

the EMSS will utilise frequency response options to these harm reduction strategies. Another limitation with the harm reduction measure utilised in the EMSS is that all strategies were shown to all participants indicating use of a drug other than alcohol and tobacco, but some strategies are somewhat drug specific, for example avoiding intravenous use to heroin, and may not have been applicable to all that answered. Unfortunately, there was no 'not applicable' option, thus these participants would have been forced to indicate 'No'. Future studies might consider showing such drug specific strategies only to those who indicated use of that particular substance.

Despite their novel application and confirmation of their validity via factor analysis, there are potential limitations associated with the positive experience and negative consequence subscales. The positive experience subscale contained considerably fewer items than the negative consequence subscale. While the use of a standardised mean score enabled comparison between the two, it is likely that important positive experiences were missing from the list. This is a particularly pertinent consideration given the far higher average frequency of positive experiences than negative consequences reported by our sample. Furthermore, the experiences that make up each subscale, arguably most notably with positive experiences, are potentially biased towards effects and outcomes associated with the use of ecstasy/MDMA. Future investigations utilising similar scales should consider incorporating a wider range of experiences that are associated with use of further substances. Another limitation with this scale is that items were only shown to individuals who indicated use of drugs other than tobacco or alcohol. This decision was made by the ALAMA-Consortium in order to focus on the effects of illicit drugs. However, given the high proportion of participants exhibiting potentially hazardous alcohol consumption discussed in Chapter 3, and the fact that avoiding combining drugs with alcohol was one of the least endorsed harm reduction strategies by the sample as a whole in this study, in hindsight an assessment of positive experiences and negative outcomes among alcohol only users would have been highly informative. In addition, that the negative experience subscale may have exhibited floor effects potentially limited the ability to detect meaningful differences between the latent classes. That differences were detected, however, highlights the need for further research into these relationships.

Finally, given the cross sectional nature of the analyses in this study no claims of a causal relationship between harm reduction strategies and positive or negative experiences can be made.

4.4.7 Conclusion

In the first study employing LCA to elicit harm reduction profiles amongst a European nightlife population, five discrete classes were identified that differed in terms of their probabilities of endorsing 30 protective behavioural strategies in the past 12 months. Harm reduction profiles were found to differ with respect to levels of polydrug use, with some support for a 'cautious' approach with some classes showing an association between higher strategy adoption and lower polydrug use. However, not all classes followed this pattern, suggesting that not all profiles fit the 'cautious' model. Controlling for polydrug use and demographic differences, the discrete harm reduction profiles also differed with regard to negative consequences and positive experiences of drug use. Higher levels of harm reduction tended to be modestly associated with negative consequences occurring less frequently, and positive experiences more frequently. The associations were considerably larger for those between harm reduction and positive experiences than negative consequences. This has important implications for tailoring and providing an acceptable positive message about harm reduction to polydrug users regularly engaging with the European nightlife scene.

Chapter 5: Longitudinal trajectories of polydrug use profiles in a European nightlife population – a multi-site latent transition analysis

5.1 Introduction

The use of methods to uncover underlying subgroups of polydrug use in a population regularly attending the European nightlife scene, such as Latent Class Analysis (LCA) employed in Chapters 3 and 4, affords the ability to identify those who may be at elevated risk of harm and traits that differentiate varying patterns of use. However, the major limitation of such methods is that their cross-sectional design precludes investigations into how polydrug use profiles may change over time. Longitudinal methods, on the other hand, are able to track temporal trajectories in polydrug use and examine what may be predictive of change. The identification of risk factors that are associated with increasing or decreasing levels of polydrug use not only further aids the identification of those most at risk, but also has the potential to inform interventions aimed to reduce drug related harm.

5.1.1 Latent Transition Analysis (LTA)

Latent Transition Analysis (LTA) is one such method that has been increasingly employed to investigate temporal changes in behavioural profiles. LTA is best conceptualised as a longitudinal extension of LCA, where subgroups, or statuses, of individuals based on certain behavioural traits are estimated at each measurement time point, and transitions in status membership are modelled (Collins & Lanza, 2009; Lanza, Patrick, & Maggs, 2010). As such, LTA is particularly well suited to modelling the trajectories of the use of multiple drugs over time.

One prominent application of LTA is to the investigation of the stability of adolescent substance use statuses (Choi, Lu, Schulte, & Temple, 2018; Maldonado-Molina & Lanza, 2010; Patrick et al., 2009; Tomczyk, Pedersen, Hanewinkel, Isensee, & Morgenstern, 2016; Zych, Rodríguez-Ruiz, Marín-López, & Llorent, 2020). For example, Zych et al (2020) identified three latent statuses of alcohol, cannabis and other drug user amongst Spanish school students which mainly remained stable over the course of 12 months, although

differences between subgroups were observed. While approximately 90% of students identified as 'Non users' or 'Frequent users' belonged to the same status at follow-up, 'Occasional users' at baseline were more likely to transition, with 18.63% and 22.86% belonging to the 'No use' and 'Frequent use' groups respectively at follow-up. Polydrug use status has also been found to remain stable across three time points 12 months apart amongst high school students in the USA, although group differences were similarly found (Choi et al., 2018). Adolescents defined as 'alcohol and moderate marijuana' and 'polysubstance' users at baseline had a probability of greater than 0.90 of remaining in these statuses at 12 and 48 month follow-up assessments. However, while still high, those in the 'mild alcohol' use class had lower probabilities of being so at time points two (0.82) and three (0.78).

High stability in status membership in samples growing from adolescence to young adulthood has also been found at two time points over the course of 18 months (Tomczyk et al., 2016) and three assessments 24 months apart (Mistry et al., 2015). Furthermore, a study exploring drug use transitions from adolescence to young adulthood over ten years found an 'alcohol dominate', 'alcohol and marijuana' and a 'poly use' status at each of six assessments, with the probability of remaining in the same status ranging from 0.58 to 0.94 for all statuses at each wave (Merrin, Thompson, & Leadbeater, 2018). However, over the course of the study, almost half of the sample had changed status membership at least once. In line with findings from studies conducted over shorter time frames (Mistry et al., 2015; Tomczyk et al., 2016), the most common transition was an increase in substance use, with 36% of the sample moving to a higher use status and 13% moving to a lower use status on at least one assessment wave.

LTA has also been employed to explore transitions in young adults and college students, with evidence suggesting that while different latent structures exist in different populations, polydrug use is largely stable in young adulthood. In a study of young Swiss males (Baggio, Studer, Deline, et al., 2014), five latent statuses emerged based on the use of 18 different drugs at baseline and follow up: 'alcohol only'; 'alcohol and tobacco'; 'alcohol, tobacco and cannabis'; 'alcohol, tobacco, cannabis and middle stage'; 'all, including final stage'. The probability of stable membership at 12 months follow-up was at least 0.84 for each status, with the exception of 'all, including final stage', which contained less than 1% of the sample at each time point. Cho and colleagues (2015) identified three statuses of polydrug use amongst US college students at baseline and 12 month follow-up

(‘low’; ‘alcohol, tobacco, cannabis’; ‘alcohol, tobacco, cannabis, other’) with the only transitions observed being 2.6% moving from ‘alcohol, tobacco, cannabis’ to ‘low’ status, while 7% progressed from ‘low’ to ‘alcohol, tobacco, cannabis’ use. The status characterised by the highest level of use was the most stable, with 100% of those defined as ‘alcohol, tobacco, cannabis, other’ users at baseline also being so at 12 month follow-up. Another study in US college students found different subgroups of polydrug user, although again these demonstrated high stability (Lanza et al., 2010). Four statuses were found with high probabilities of stability at 9 month follow-up: ‘non users’ (0.90); ‘cigarette smokers’ (0.65); ‘binge drinkers’ (0.83); ‘binge drinkers with marijuana’ (0.94). While some transitions were observed, no demographic or personality traits were predictive of change (Lanza et al., 2010).

5.1.2 Longitudinal studies of drug use in nightlife populations

Given that high rates of polydrug use are observed amongst young adults regularly engaging with nightlife, as discussed in Chapter 3, it is apparent that this would be an ideal target population for investigations into transitions of drug use utilising LTA. However, to the author’s knowledge, this has yet to be conducted, while longitudinal associations between demographic and personality traits and polydrug use in nightlife populations utilising other methods further highlight that this would be a valuable addition to the literature.

Indeed, the level of engagement with the nightlife scene has been shown to be associated with temporal changes in drug use. Monthly attendance at nightclubs has been shown to be predictive of monthly ecstasy use (Leslie et al., 2015) and hazardous alcohol consumption (Leslie et al., 2016) amongst young adult stimulant users in Australia at 30 month follow-up, over and above attendance at festivals, live music venues, pubs/bars and house parties. Music genre has also been associated with ecstasy use in the same sample, with attendance of electronic dance music events predicting sustained monthly use over the course of 30 months (Smirnov et al., 2013).

While studies examining the longitudinal patterns of certain drugs (ecstasy, alcohol) have found an influence of nightlife engagement, use of particular drugs has been associated with the use of others over time. For example, alcohol use has been associated with more consistent use of cocaine over the course of 12 months (Ramo et al., 2011), while frequent use of ecstasy over time has been associated with more frequent alcohol, cannabis and

methamphetamine use (Leslie et al., 2015, 2016; Smirnov et al., 2013). These findings demonstrate the need to consider the temporal associations between drug use and nightlife engagement in the context of polydrug consumption.

Another area that has received little focus within samples of polydrug users is risk perception, although individual drugs associated with use in the nightlife scene have been studied. For example, a LCA conducted by Martins et al (2011) amongst ecstasy users in the USA found five classes differentiated by the level of risk to health and related issues attributed to their ecstasy use. Half of the sample perceived their ecstasy use to carry low (28.9%) or moderate (21.1%) risk, while groups defined by perceived sexual-related risk (25.6%), memory and cognitive problems (11.9%) and risk to all areas (12.4%) were also identified. Compared to those who perceived low level of ecstasy related risk, those identified as perceiving problems in all areas were more likely to report moderate or severe depressive symptoms and 50 or more lifetime occasions of ecstasy use. However, given the cross-sectional study design, the effect of risk perception on ecstasy use behaviour could not be ascertained.

Findings from longitudinal studies suggest that risk perception may indeed be predictive of later ecstasy use. In a study of young adult club drug users in the USA and Australia, Leung and colleagues (2010) assessed perceptions of risk by asking participants to rate the danger of taking ecstasy once a week on a five point scale from “Not dangerous at all” to “Extremely dangerous”, and assessed ecstasy use at two week follow-up. Low risk perception was significantly associated with an increase in the likelihood of ecstasy use between the two assessments (adjusted OR 1.35; 95% CI 1.08-1.69). Furthermore, those perceiving weekly use to be “Not dangerous at all” were over three times more likely to have used ecstasy at follow-up than those rating it “Extremely dangerous”. Similarly, in a separate study of Australian stimulant users (Smirnov et al., 2013), those who perceived ecstasy to be “very risky” were less likely to be in the high or intermediate using groups than the low use group at 30 month follow-up (RR 0.49; 95% CI: 0.30-0.81).

However, limitations with both studies mean results should be interpreted with some caution. Firstly, Leung and colleagues’ (2010) short follow-up period prevents any conclusions being drawn about the long term effect of risk perception on behaviour, although evidence from Smirnov et al (2013) suggests that there may longer term associations. Secondly, both studies used a single item relating to the risk of ecstasy use, which may not have captured all aspects that might contribute to the perceptions of drug

related risk. Finally, the majority of the samples in both studies did not use ecstasy in isolation, thus the influence of risk perception on polydrug use rather than that specific to ecstasy might be more informative for the design of salient interventions.

The objective of this study was to address the gaps in the literature raised above with respect to longitudinal trajectories of polydrug use in a European nightlife population, and the association with risk perception. Specifically, this study had three aims:

1. Utilise LTA to investigate 12 month polydrug use trajectories amongst a sample of young European adults regularly engaging with the nightlife scene.
2. Determine the association between polydrug use profiles at baseline and follow-up with risk perception, nightlife engagement and demographic characteristics.
3. Examine the transitions in past 12 month polydrug use profiles between baseline and 12 month follow-up, and the associations with risk perception, nightlife engagement and demographic characteristics.

5.2 Methods

5.2.1 Participants

The Electronic Music Scene Survey (EMSS) was a longitudinal, online survey investigating drug use trajectories over 12 months in young adults regularly engaging with the European nightlife scene. A detailed discussion of the study development, design, recruitment and inclusion criteria can be found in Chapter 1. The sample for this study comprised of 2,897 young adults living in Belgium, Italy, Netherlands, Sweden or the UK who completed both baseline and follow-up surveys.

Ethical approval was granted in the UK by UCL Research Ethics Committee (project ID: 10437/001).

5.2.2 Measures

5.2.2.1 Drug use

At both baseline and follow-up, participants indicated whether they had used any of 21 licit and illicit drugs in the past 12 months. Responses were used to estimate latent profiles of polydrug use at both time-points.

5.2.2.2 Risk perception

The perceived risk of harm of drug use was assessed at baseline and follow-up using a scale similar to that used by the European School Survey Project on Alcohol and Other Drugs research group (ESPAD; e.g. Andreas, 2019). Participants were asked the following question for each of the 12 items listed below:

“How much do you think people risk harming themselves (physically, or in other ways), if they...

1. Smoke cigarettes occasionally
2. Smoke one or more packs of cigarettes per day
3. Have one or two alcohol drinks nearly every day
4. Have four or five alcoholic drinks nearly every day
5. Have drinks in one occasion nearly every weekend
6. Try marijuana or hashish (cannabis) once or twice
7. Smoke marijuana or hashish (cannabis) occasionally
8. Smoke marijuana or hashish (cannabis) regularly
9. Try ecstasy once or twice
10. Take ecstasy regularly
11. Try an amphetamine (uppers, pep pills, bennie, speed) once or twice
12. Take amphetamines regularly”

Response options were “No risk (0)”, “Slight risk (1)”, “Moderate risk (2)”, “Great risk (3)” and “Don’t know (4)”. To create a risk perception summary score, item responses were summed, excluding “Don’t know” answers, resulting in a score ranging from 0 to 36 with higher scores indicating a greater perception of risk.

5.2.2.3 Demographic characteristics

Age, gender, country of residence, highest level of education, number of electronic dance music events attended in the past 12 months and wellbeing as measured by WHO-5 scores were collected at baseline and follow-up.

To allow an examination of whether demographic changes influenced polydrug use profiles, additional variables were created to reflect whether a participant had moved country, increased their level of education and the change in the number of events they attended in the past 12 months from baseline to follow-up.

5.2.3 Statistical analysis

5.2.3.1 Attrition analysis

In order to investigate the effect of attrition on the final sample, follow-up survey completers (n=2897) were compared to completers of the baseline but not the follow-up survey (n=5148) with respect to demographics and past 12 month drug use. Specifically, chi-squared tests were performed to ascertain differences in gender, country of residence, highest level of education and past 12 month drug use. T-tests were conducted for differences in age, event attendance and mean past 12 month drug use frequency. To account for multiple comparisons, statistical significance was determined using Bonferroni corrected p-values.

5.2.3.2 Latent transition analysis

Latent Transition Analysis (LTA) is a statistical method that is a longitudinal extension of Latent Class Analysis (LCA) employed in Chapters 3 and 4. LTA identifies subgroups, or statuses, of individuals at different points in time based upon a range of behavioural indicator variables, in this instance the past 12 month use of 21 different drugs. Furthermore, LTA models transitions in status membership over time and provides three key parameter estimates of interest: firstly, item response probabilities for each latent status measured at each time point, showing, for example, the probabilities of endorsing past 12 month use of each drug; secondly, the sample size and membership probabilities of each latent status at each time point; thirdly, transition probabilities reflecting the probability of changing from one latent status at one time point to a different status at another (Lanza et al., 2010; Nylund, 2007). Measurement invariance can also be formally tested to assess whether the same underlying latent structure with regard to the number

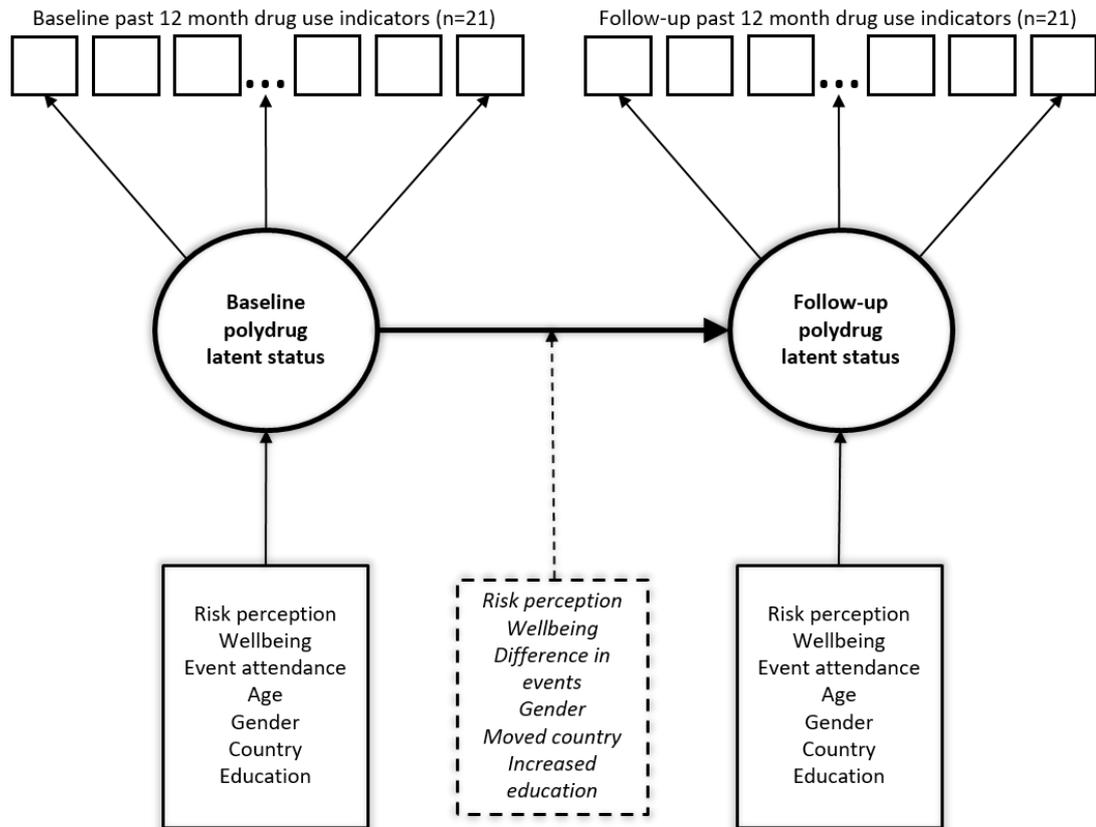
and interpretability of identified latent statuses can be used at each time point, or whether different measurement models at different times better explain the data. In effect, this involves testing whether the item response probabilities for each status can be considered equal across time, such that the only transitions modelled are those reflecting changes in status membership and not the underlying meaning of each status, or whether different profile patterns emerge at different measurement points.

In order to determine the latent status model that best fit our data, a series of models postulating two to seven statuses were fit at both baseline and follow-up, using past 12 month drug use measured at each time point as indicator variables. To determine the optimum number of classes, models at each time point were examined using fit indices (AIC; BIC; adjusted BIC), the Lo-Mendell-Rubin (LMR) likelihood ratio test and theoretical interpretability of each solution.

Once the best fitting model at each time-point had been identified, measurement invariance was tested to see whether the same latent structure could be assumed to exist at baseline and follow-up. This involved fitting a model in which the item response probabilities were constrained to be the same at baseline and follow-up (measurement invariance model), and comparing this to a model in which the probabilities were allowed to be freely estimated at each time-point (measurement variance model). A likelihood ratio test was performed in which the difference in log-likelihood between the invariance and variance models was compared to a chi-squared distribution with degrees of freedom equal to the difference in parameters between the two models. A non-significant p-value resulting from this test indicates that the measurement invariance model is the better-fitting, and should be retained in favour of the measurement variance model.

After determining whether measurement invariance could be assumed, latent status at follow-up was regressed on latent status at baseline to estimate the transition probabilities between latent statuses over time. This was then extended to a logistic regression model that included covariates to investigate the association between latent status and risk perception and demographic characteristics at both time points. A final model was then fit with risk perception and changes in demographic traits predicting transitions in latent status membership between baseline and follow-up. The diagram depicting the overall modelling approach performed in this study is displayed in Figure 5.1. All analyses were performed in Mplus version 8.2 (Muthén & Muthén, 2018) and SPSS version 26 (IBM Corp, 2017).

Figure 5.1: Diagram of modelling approach to investigate the relationship between latent status, risk perception, demographic characteristics and transitions between baseline and follow-up



5.3 Results

5.3.1 Sample characteristics

The demographic characteristics measured at baseline and follow-up are displayed in Table 5.1. Inspection of this table shows similar mean scores and proportions at baseline and follow-up for the vast majority of sociodemographic characteristics. The largest difference was seen in levels of education, with the most notable change being the increase in those reporting holding a university degree or equivalent at follow-up.

Table 5.1: Demographic characteristics at baseline and follow-up

	Baseline		Follow-up	
	%	(N)	%	(N)
Gender*				
Female	33.00	(956)	33.10	(959)
Male	66.24	(1919)	66.42	(1924)
Other	0.76	(22)	0.48	(14)
Country of residence				
Belgium	17.09	(495)	16.98	(492)
Italy	11.77	(341)	11.56	(335)
Netherlands	28.99	(840)	28.58	(828)
Sweden	17.19	(498)	16.64	(482)
UK	24.96	(723)	24.24	(702)
Other			2.00	(58)
Moved country at follow-up			2.80	(81)
Education				
Primary school / key stage 1 and 2	1.36	(39)	0.24	(7)
Secondary school / key stage 3	12.10	(348)	8.61	(247)
GCSE / A-level / key stage 4	52.54	(1511)	46.97	(1347)
University degree / NVQ4 or higher	34.00	(978)	44.18	(1267)
Increased education at follow-up			15.22	(441)
	Mean	(SD)	Mean	(SD)
Age	23.83	(4.46)	24.80	(4.47)
Events past 12 months	18.04	(16.46)	18.14	(22.14)
Risk perception	21.69	(5.34)	21.90	(5.23)
WHO-5	62.19	(17.91)	61.91	(18.45)

Abbreviations: UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO – World Health Organisation

*NB differences in numbers in gender are due to 8 individuals who identified as ‘other’ at baseline identifying as either male (5) or female (3) at follow-up

5.3.2 Attrition analysis

Tables 5.2 to 5.4 show the results of comparisons of follow-up completers' and non-completers' demographic characteristics and drug use as measured at baseline. With regard to demographics, follow-up completers were approximately half a year older on average and attended fewer events in the past 12 months. A higher proportion of completers were women and had higher levels of education, while differences in country of residence were also observed.

Table 5.3 displays the results of comparisons of the proportion of follow-up completers and non-completers endorsing past 12 month use of 21 drugs. The only Bonferroni corrected significant results show that fewer completers used tobacco, while a higher proportion used 4FA, thus there was very limited evidence of any systematic differences associated with attrition. Furthermore, attrition did not seem to overly affect estimates of drug use frequency at follow-up, as the only significant differences were found for alcohol, tobacco and cocaine (Table 5.4), in which completers used each less frequently on average than survey non-completers.

5.3.3 LTA model selection

Table 5.5 displays the fit indices and LMR p-values for two to seven class solutions fit at baseline and follow-up. Fitting models with increasing number of classes failed to reach a global solution, in that fit indices continued to decrease as a model postulating $k+1$ classes was fit to the data. However, as discussed in Chapters 3 and 4, this is not uncommon in latent modelling, and it is recommended to inspect the indices plot to investigate the magnitude of reduction, while also considering the interpretation of the emergent solutions. Figures 5.2 and 5.3 plot the fit indices at baseline and follow-up, and show the 'elbow' at which the magnitude of decrease dramatically reduced was when fitting a three class model at both time points. Furthermore, the three class solution was chosen at each time point as it offered the best theoretical interpretability and utility for investigating transitions in latent status membership.

Table 5.2: Attrition analysis – demographic comparisons between follow-up survey completers and non-completers

	Follow-up non completers (N=5148)		Follow-up completers (N=2897)		t	p
	Mean	(SD)	Mean	(SD)		
Age	23.38	(4.22)	23.83	(4.46)	-4.51	<0.001
Events past 12 months	19.31	(20.34)	18.04	(16.46)	2.88	0.004
Risk perception	21.64	(5.58)	21.69	(5.34)	-0.44	0.66
WHO-5	62.93	(18.35)	62.19	(18.82)	1.72	0.09
	%	(n)	%	(n)	X ²	p
Gender						
Male	70.63	(3636)	66.24	(1919)		
Female	28.77	(1481)	33.00	(956)	16.82	<0.001
Other	0.60	(31)	0.76	(22)		
Country of residence						
Belgium	16.51	(850)	17.09	(495)		
Italy	15.66	(806)	11.77	(341)		
Netherlands	24.92	(1283)	28.99	(840)	32.43	<0.001
Sweden	16.96	(873)	17.19	(498)		
UK	25.95	(1336)	24.96	(723)		
Education						
Primary school / key stage 1 and 2	1.72	(87)	1.36	(39)		
Secondary school / key stage 3	14.97	(757)	12.10	(348)		
GCSE / A-level / key stage 4	54.25	(2744)	52.54	(1511)	30.94	<0.001
University degree / NVQ4 or higher	29.06	(1470)	34.00	(978)		

Significant Bonferroni corrected results (0.05 / 8 = 0.0063) highlighted in bold.

Abbreviations: SD – standard deviation; UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO – World Health Organisation

Table 5.3: Attrition analysis – comparison of past 12 month drug use between follow-up survey completers and non-completers

	Follow-up non completers (N=5148)		Follow-up completers (N=2897)		X ²	p
	%	(n)	%	(n)		
Alcohol	95.92	(4938)	96.13	(2785)	0.22	0.64
Tobacco	72.51	(3733)	68.04	(1971)	18.02	<0.001
Cannabis	64.14	(3302)	62.31	(1805)	2.69	0.10
Ecstasy / MDMA	52.16	(2685)	53.68	(1555)	1.72	0.19
Cocaine	38.58	(1986)	36.42	(1055)	3.68	0.06
Amphetamines	24.26	(1249)	23.30	(675)	0.94	0.33
4FA	9.23	(475)	11.49	(333)	10.55	0.001
LSD	13.93	(717)	13.63	(395)	0.13	0.72
Magic mushrooms	15.64	(805)	16.33	(473)	0.66	0.42
Synthetic hallucinogens	11.71	(603)	13.60	(394)	6.08	0.02
Ketamine	27.10	(1395)	25.68	(744)	1.91	0.17
Nitrous oxide	36.15	(1861)	34.48	(999)	2.25	0.13
Benzodiazepines	10.86	(559)	10.56	(306)	0.17	0.68
Amyl nitrates	11.50	(592)	11.91	(345)	0.30	0.58
Prescription opioids	5.67	(292)	5.25	(152)	0.64	0.42
GHB	4.14	(213)	4.45	(129)	0.45	0.50
DMT	2.84	(146)	2.93	(85)	0.06	0.80
Mephedrone	2.00	(103)	1.86	(54)	0.18	0.67
Synthetic dissociatives	1.48	(76)	1.52	(44)	0.02	0.88
Synthetic cannabinoids	1.20	(62)	1.14	(33)	0.07	0.80
Heroin	0.56	(29)	0.17	(5)	6.73	0.01

Significant Bonferroni corrected results (0.05 / 21 = 0.0024) highlighted in bold.

Abbreviations: MDMA - 3,4-Methylenedioxyamphetamine; 4FA - 4-Fluoroamphetamine; LSD - Lysergic acid diethylamide; GHB - Gamma-hydroxybutyrate; DMT - N,N-Dimethyltryptamine.

Table 5.4: Attrition analysis – comparison of mean past 12 month drug use frequency between follow-up survey completers and non-completers

	Follow-up non completers (N=5148)		Follow-up completers (N=2897)		t	p
	Mean	(SD)	Mean	(SD)		
Alcohol	4.48	(1.48)	4.49	(1.44)	-0.31	0.76
Tobacco	3.35	(2.58)	2.93	(2.54)	7.03	<0.001
Cannabis	2.17	(2.24)	1.88	(2.06)	5.87	<0.001
Ecstasy / MDMA	1.11	(1.29)	1.10	(1.25)	0.34	0.74
Cocaine	0.79	(1.26)	0.70	(1.18)	3.15	0.002
Amphetamines	0.50	(1.10)	0.47	(1.04)	1.25	0.21
4FA	0.15	(0.54)	0.19	(0.60)	-2.60	0.009
LSD	0.19	(0.57)	0.19	(0.54)	0.60	0.55
Magic mushrooms	0.19	(0.49)	0.19	(0.47)	-0.12	0.91
Synthetic hallucinogens	0.17	(0.53)	0.19	(0.55)	-1.97	0.047
Ketamine	0.57	(1.15)	0.50	(1.04)	2.49	0.013
Nitrous oxide	0.68	(1.12)	0.64	(1.09)	1.49	0.14
Benzodiazepines	0.24	(0.85)	0.23	(0.81)	0.83	0.41
Amyl nitrates	0.19	(0.63)	0.19	(0.65)	-0.51	0.61
Prescription opioids	0.13	(0.67)	0.12	(0.66)	0.32	0.75
GHB	0.08	(0.44)	0.08	(0.48)	-0.89	0.38
DMT	0.04	(0.26)	0.04	(0.26)	-0.23	0.82
Mephedrone	0.04	(0.33)	0.03	(0.24)	1.47	0.14
Synthetic dissociatives	0.03	(0.24)	0.02	(0.22)	0.26	0.79
Synthetic cannabinoids	0.02	(0.27)	0.02	(0.24)	0.45	0.65
Heroin	0.02	(0.26)	0.01	(0.16)	1.93	0.053

Significant Bonferroni corrected results ($0.05 / 21 = 0.0024$) highlighted in bold.

Abbreviations: SD – Standard Deviation; MDMA - 3,4-Methylenedioxymethamphetamine; 4FA - 4-Fluoroamphetamine; LSD - Lysergic acid diethylamide; GHB - Gamma-hydroxybutyrate; DMT - N,N-Dimethyltryptamine.

Table 5.5: Fit indices for two to seven class solutions at baseline and follow-up

Classes	AIC	BIC	Adjusted BIC	Entropy	LMR p-value
Baseline					
2	36571.358	36828.129	36691.503	0.887	<0.001
3	35563.383	35951.526	35744.997	0.826	<0.001
4	35280.496	35800.011	35523.580	0.764	<0.001
5	35100.231	35751.117	35404.785	0.760	0.266
6	34906.644	35688.902	35272.667	0.786	0.023
7	34788.629	35702.258	35216.121	0.763	0.180
Follow-up					
2	36924.355	37181.126	37044.500	0.894	<0.001
3	35910.983	36299.126	36092.597	0.825	<0.001
4	35635.709	36155.223	35878.793	0.778	<0.001
5	35440.034	36090.920	35744.587	0.766	0.294
6	35266.602	36048.860	35632.625	0.764	0.280
7	35092.478	36006.107	35519.970	0.777	0.100

Chosen 3 class solutions highlighted in bold

AIC – Akaike Information Criterion; BIC – Bayesian Information Criterion; LMR – Lo-Mendell-Rubin

Figure 5.2: Information criterion fit indices plot at baseline

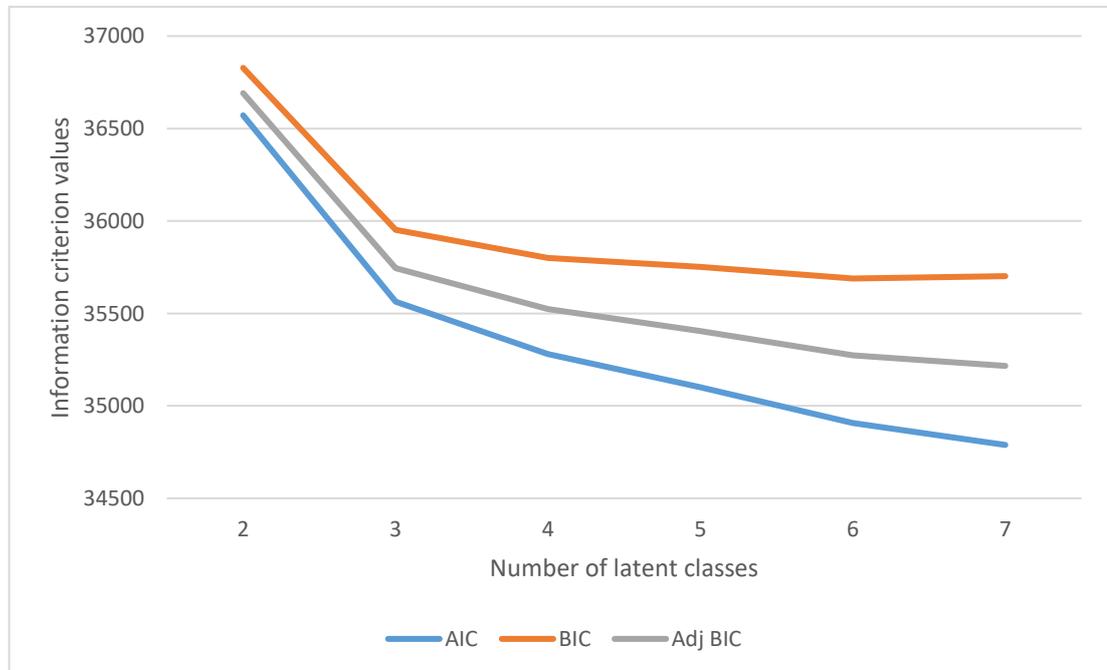


Figure 5.3: Information criterion fit indices plot at follow-up

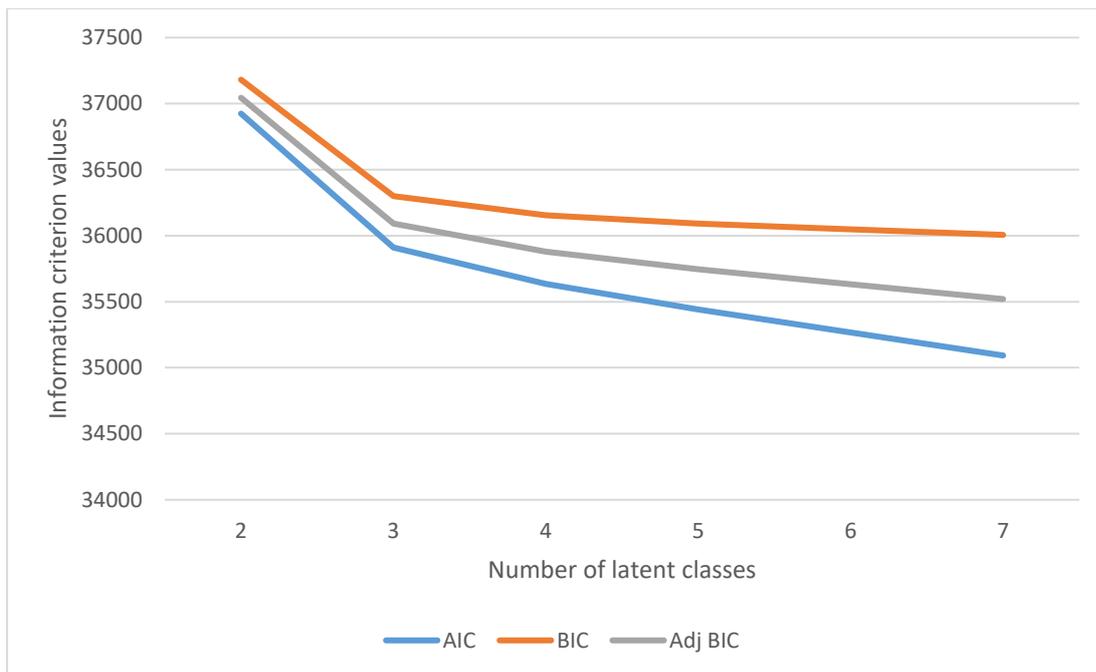


Figure 5.4 plots the item response probabilities of the three class models at baseline and follow-up. Profiles were very similar with respect to the probability of past 12 month drug use endorsement at both time-points, suggesting measurement invariance may be a reasonable assumption. Indeed, the likelihood ratio test comparing a model in which response probabilities were constrained to be equal over time to one that allowed them to be freely estimated was non-significant ($\chi^2(63)=82.46$, $p=0.051$), confirming measurement invariance could be assumed. Furthermore, the adjusted BIC value of the invariance model (71700.495) was lower than that of the variance model (71837.595), providing further evidence that this was a better fitting model and that the same latent structure can be assumed to be consistent over time.

Figure 5.4: Item endorsement probabilities of the three status solution at baseline and follow-up

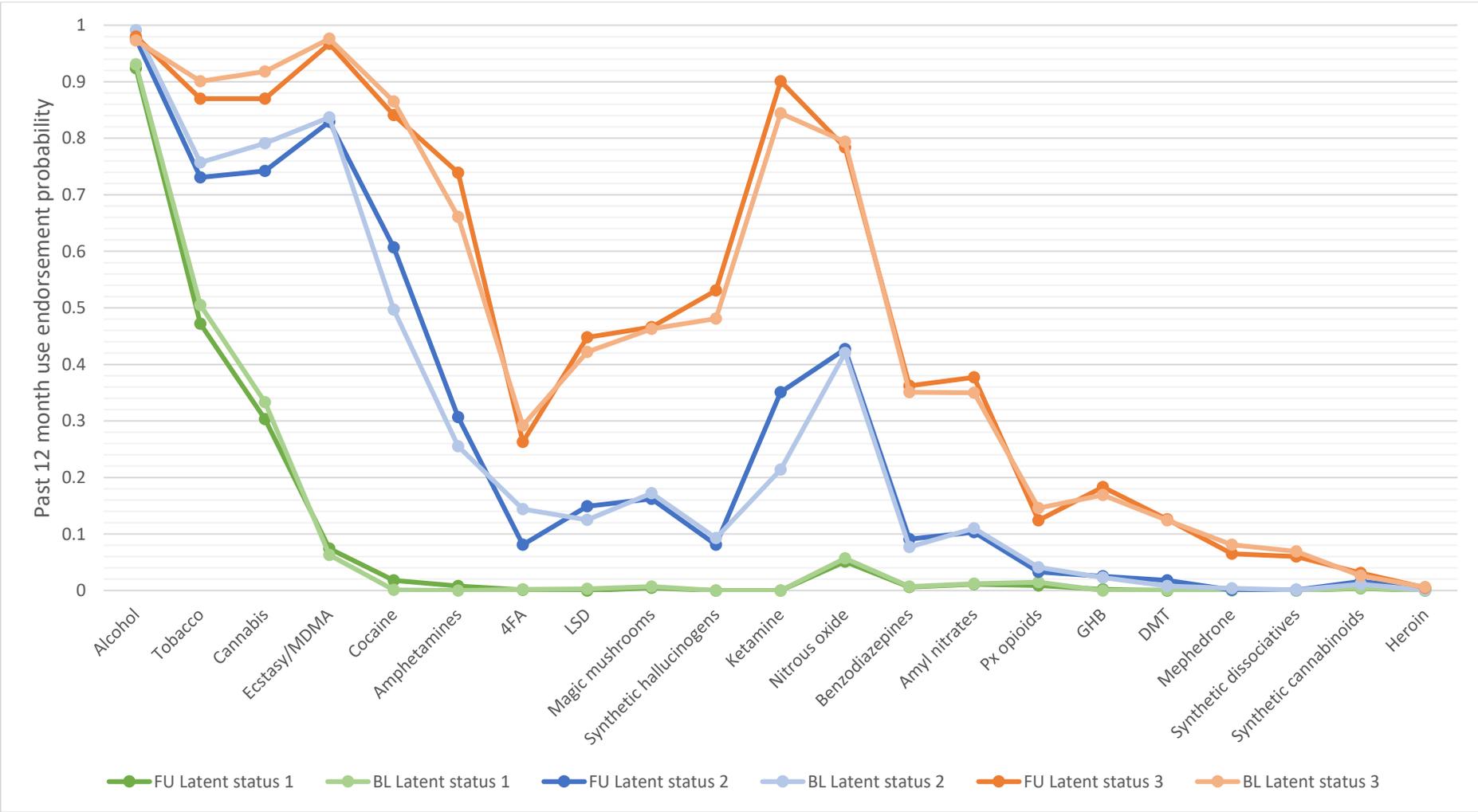
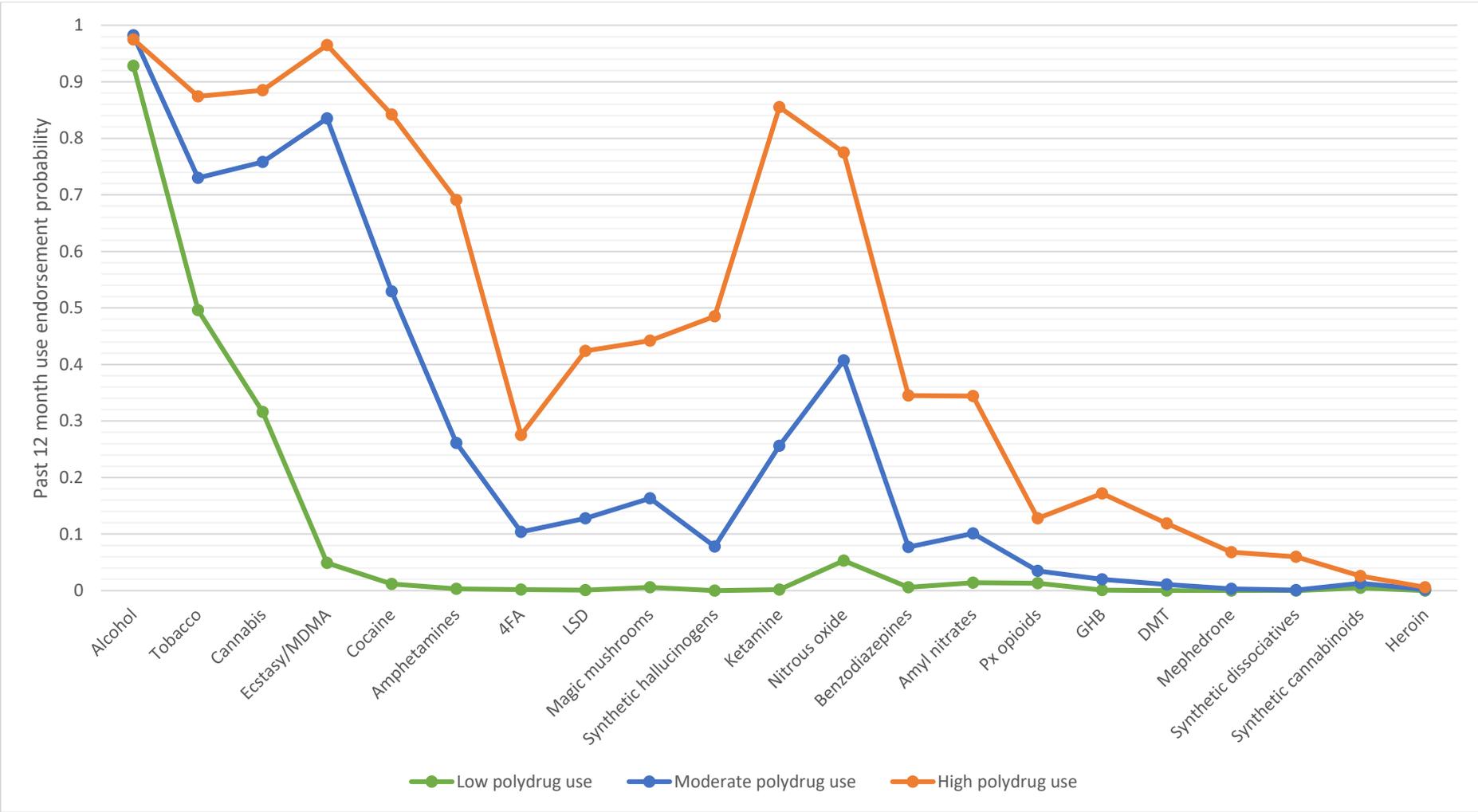


Figure 5.5: Latent status item endorsement probabilities, fixed to be equal at baseline and follow-up



5.3.4 Latent status description

The endorsement probabilities of the chosen three status solution fixed to be equal at baseline and follow-up are displayed in Figure 5.5, and suggest that statuses can be labelled and described as follows:

1. *Low polydrug use*: High probabilities of endorsing past 12 month alcohol use; moderate probabilities of endorsing past 12 month use of tobacco and cannabis; very low probabilities of endorsing use of any of the remaining 18 drugs.
2. *Moderate polydrug use*: High probabilities of past 12 month alcohol, tobacco, cannabis and ecstasy use; moderate probabilities of past 12 month use of cocaine and nitrous oxide; moderate to low probabilities of past 12 month ketamine and amphetamine use.
3. *High polydrug use*: High probabilities of past 12 month use of alcohol, tobacco, cannabis, ecstasy, cocaine, ketamine, nitrous oxide and amphetamines; moderate probabilities of use of synthetic hallucinogens, magic mushrooms, LSD, benzodiazepines, amyl nitrates and 4-fluoroamphetamine (4FA).

The proportions of participants belonging to each latent status at baseline and follow-up are displayed in Table 5.6.

5.3.5 Associations between latent status and risk perception

The mean risk perception scores measured at baseline and follow-up by latent status are displayed in Table 5.6, while the mean item scores by latent status at baseline are displayed in Table 5.7. Risk perception scores were similar for each status at baseline and follow-up, indicating risk perception may be stable over time. Furthermore, at both time-points, increasing levels of polydrug use as measured by latent status membership was associated with lower mean risk perception scores.

Table 5.6: Demographic characteristics and risk perception scores by latent status at baseline and follow-up

	Baseline				Follow-up			
	Low	Moderate	High	Omnibus test	Low	Moderate	High	Omnibus test
N (%)	1241 (42.84)	1024 (35.34)	632 (21.82)		1230 (42.46)	1018 (35.14)	649 (22.40)	
Age	23.38 (± 0.26)	24.33 (± 0.27)	23.92 (± 0.33)	$F_{(2894,2)}=13.08,$ $p<0.001$	24.37 (± 0.26)	25.29 (± 0.26)	24.83 (± 0.33)	$F_{(2894,2)}=12.02,$ $p<0.001$
Gender								
Female	30.94%	36.52%	31.33%	$\chi^2_{(4)}=10.22,$ $p=0.037$	30.24%	37.72%	31.28%	$\chi^2_{(4)}=17.43,$ $p=0.002$
Male	68.09%	62.99%	67.88%		69.11%	62.08%	68.10%	
Other	0.97%	0.49%	0.79%		0.65%	0.20%	0.62%	
Country of residence								
Belgium	26.03%	11.82%	8.07%	$\chi^2_{(8)}=671.51,$ $p<0.001$	25.85%	12.38%	7.40%	$\chi^2_{(6)}=55.78,$ $p<0.001$
Italy	23.21%	4.39%	1.27%		22.76%	4.72%	1.08%	
Netherlands	13.54%	37.11%	46.20%		13.58%	34.97%	47.00%	
Sweden	22.48%	15.04%	10.28%		21.79%	14.73%	9.86%	
UK	14.75%	31.64%	34.18%		14.47%	31.04%	32.05%	
Other					1.55%	2.16%	2.61%	

	Baseline				Follow-up			
	Low	Moderate	High	Omnibus test	Low	Moderate	High	Omnibus test
Education								
Primary school / key stage 1 and 2	1.79%	0.99%	1.11%		0.41%	0.00%	0.31%	
Secondary school / key stage 3	15.70%	9.75%	8.86%	$\chi^2_{(6)}=65.28,$ $p<0.001$	10.86%	7.14%	6.67%	$\chi^2_{(6)}=55.78,$ $p<0.001$
GCSE / A-level / key stage 4	55.49%	48.28%	53.64%		51.36%	40.97%	48.06%	
University degree / NVQ4 or higher	27.02%	40.99%	36.39%		37.37%	51.89%	44.96%	
Events past 12 months	16.66 (± 0.93)	17.60 (± 0.91)	21.47 (± 1.40)	$F_{(2894,2)}=18.67,$ $p<0.001$	15.94 (± 1.26)	18.15 (± 1.33)	22.30 (± 1.66)	$F_{(2894,2)}= 17.74,$ $p<0.001$
Risk perception	24.19 (± 0.31)	20.10 (± 0.26)	19.37 (± 0.32)	$F_{(2894,2)}=289.64,$ $p<0.001$	24.14 (± 0.33)	20.54 (± 0.25)	19.81 (± 0.29)	$F_{(2894,2)}=231.19,$ $p<0.001$
WHO-5	60.49 (± 1.09)	63.67 (± 1.12)	63.12 (± 0.69)	$F_{(2894,2)}=9.04,$ $p<0.001$	60.83 (± 1.08)	62.73 (± 1.11)	62.67 (± 1.34)	$F_{(2894,2)}=3.68,$ $p=0.03$

Abbreviations: UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO – World Health Organisation

Table 5.7: Mean individual risk perception scale item scores at baseline by latent status

	Low PD use Mean (95% CI)	Moderate PD use Mean (95% CI)	High PD use Mean (95% CI)	F	p
Baseline					
Smoke cigarettes occasionally	1.80 (1.76, 1.85)	1.73 (1.68, 1.78)	1.71 (1.65, 1.77)	3.83	0.022
Smoke 1 or 2 packs of cigarettes per day	2.86 (2.84, 2.89)	2.91 (2.89, 2.93)	2.90 (2.87, 2.93)	3.80	0.023
Have 1 or 2 alcohol drinks nearly every day	1.99 (1.94, 2.04)	1.89 (1.84, 1.94)	1.85 (1.79, 1.91)	7.52	<0.001
Have 4 or 5 alcohol drinks nearly every day	2.77 (2.74, 2.80)	2.78 (2.75, 2.81)	2.77 (2.73, 2.80)	0.162	0.851
Have 5 drinks in one occasion nearly every weekend	2.03 (1.99, 2.08)	1.89 (1.84, 1.94)	1.93 (1.87, 1.99)	9.63	<0.001
Try cannabis once or twice	0.75 (0.70, 0.80)	0.26 (0.23, 0.29)	0.23 (0.19, 0.27)	186.11	<0.001
Smoke cannabis occasionally	1.13 (1.08, 1.18)	0.72 (0.68, 0.76)	0.67 (0.62, 0.72)	117.15	<0.001
Smoke cannabis regularly	1.98 (1.93, 2.03)	1.66 (1.61, 1.71)	1.58 (1.52, 1.64)	63.09	<0.001
Try ecstasy once or twice	1.66 (1.60, 1.72)	0.69 (0.65, 0.74)	0.55 (0.50, 0.60)	491.05	<0.001
Take ecstasy regularly	2.55 (2.50, 2.59)	1.98 (1.93, 2.04)	1.88 (1.81, 1.94)	196.07	<0.001
Try amphetamines once or twice	1.98 (1.93, 2.04)	1.13 (1.08, 1.19)	0.94 (0.88, 1.00)	354.97	<0.001
Take amphetamines regularly	2.69 (2.65, 2.73)	2.46 (2.42, 2.51)	2.36 (2.30, 2.42)	46.33	<0.001
Follow-up					
Smoke cigarettes occasionally	1.81 (1.76, 1.86)	1.79 (1.74, 1.84)	1.83 (1.77, 1.89)	0.53	0.591
Smoke 1 or 2 packs of cigarettes per day	2.86 (2.84, 2.89)	2.89 (2.87, 2.92)	2.92 (2.90, 2.95)	5.09	0.006
Have 1 or 2 alcohol drinks nearly every day	1.91 (1.86, 1.95)	1.87 (1.83, 1.92)	1.89 (1.83, 1.95)	0.533	0.587
Have 4 or 5 alcohol drinks nearly every day	2.76 (2.73, 2.79)	2.81 (2.78, 2.84)	2.80 (2.77, 2.84)	3.02	0.049
Have 5 drinks in one occasion nearly every weekend	2.09 (2.04, 2.14)	1.97 (1.92, 2.02)	2.03 (1.97, 2.09)	6.83	0.001
Try cannabis once or twice	0.75 (0.70, 0.80)	0.30 (0.27, 0.33)	0.23 (0.20, 0.27)	169.43	<0.001
Smoke cannabis occasionally	1.13 (1.08, 1.18)	0.78 (0.74, 0.82)	0.69 (0.64, 0.74)	101.44	<0.001
Smoke cannabis regularly	1.98 (1.93, 2.03)	1.71 (1.66, 1.76)	1.63 (1.57, 1.68)	47.10	<0.001
Try ecstasy once or twice	1.66 (1.60, 1.72)	0.72 (0.68, 0.77)	0.52 (0.48, 0.57)	481.88	<0.001
Take ecstasy regularly	2.54 (2.50, 2.59)	2.06 (2.01, 2.11)	1.92 (1.86, 1.99)	160.16	<0.001
Try amphetamines once or twice	1.98 (1.92, 2.03)	1.13 (1.08, 1.19)	0.90 (0.84, 0.96)	373.30	<0.001
Take amphetamines regularly	2.67 (2.63, 2.72)	2.51 (2.46, 2.55)	2.44 (2.39, 2.49)	24.97	<0.001
Significant Bonferroni corrected differences (0.05 / 12 = 0.0042) highlighted in bold					

Tables 5.8 and 5.9 show the results from the logistic regression model of the association between risk perception and latent status membership, adjusted for demographic characteristics. At both baseline (Table 5.8) and follow-up (Table 5.9), a one unit increase in mean risk perception scores was associated with significantly lower odds of being a member of either the *Moderate or High polydrug use* status compared to the *Low polydrug use* status. As such, an increase in risk perception was associated with decreasing odds of higher levels of polydrug use. The strength of this association was similar for the *Moderate vs Low* and *High vs Low* comparisons at both time points.

5.3.6 Associations between latent status and demographic characteristics

Demographic characteristics for each latent status at baseline and follow-up are displayed in Table 5.6. All omnibus tests yielded significant results, demonstrating good discriminant validity of the chosen three class solution at both baseline and follow-up. Tables 5.8 and 5.9 display the associations between demographic characteristics and latent status at baseline and follow-up, adjusting for all variables in the model. The most robust association was found between latent status membership and the number of events attended in the past 12 months. An increase in the average number of events attended in the past 12 months was associated with lower odds of being a member of the *Low polydrug use* status rather than the *High polydrug use* status at baseline, and both the *Moderate and High polydrug use* status' at follow-up.

With regard to country of residence, at baseline participants were significantly less likely to be members of the *Moderate or High polydrug use* class if living in Belgium, Italy or Sweden compared to the UK. This association was not as robust at follow-up, with residents of Italy less likely to be in the *High* than the *Low polydrug use* status than those living in the UK, while living in the Netherlands rather than the UK was associated with higher odds of belonging to the *High* than *Low polydrug use* status. Similarly, age was only significantly associated with status membership at baseline, with a year's increase in age associated with increased odds of belonging to both the *Moderate and High polydrug use* compared to the *Low polydrug use* status. Gender was also found to be associated with latent status membership, in that members of the *Moderate polydrug use* status were more likely to be female than *Low polydrug use* members at both baseline and follow-up. The only association between wellbeing, as indexed by WHO-5 scores, and status membership was found at baseline whereby higher wellbeing scores were found amongst members of the *Moderate* compared to the *Low polydrug use* status.

Table 5.8: Results from risk perception and well-being logistic regression models at baseline, adjusted for demographic characteristics

	Coefficient	S.E.	p	OR	(95% CI)
Moderate PD use vs Low PD use					
Risk perception	-0.147	0.013	<0.001	0.86	(0.84, 0.88)
WHO-5	0.010	0.003	0.002	1.01	(1.003, 1.02)
Events past 12 months	0.008	0.005	0.088	1.01	(0.99, 1.02)
Age	0.036	0.017	0.035	1.04	(1.003, 1.07)
Gender					
Female	Reference				
Male	-0.279	0.122	0.023	0.76	(0.60, 0.96)
Country					
Belgium	-1.395	0.177	<0.001	0.25	(0.18, 0.35)
Italy	-2.088	0.220	<0.001	0.12	(0.08, 0.19)
Netherlands	0.312	0.180	0.083	1.37	(0.96, 1.94)
Sweden	-1.254	0.217	<0.001	0.29	(0.19, 0.44)
UK	Reference				
Education					
Secondary school / key stage 3 or less	-0.093	0.222	0.675	0.91	(0.59, 1.41)
GCSE / A-level / key stage 4	-0.256	0.147	0.082	0.77	(0.58, 1.03)
University degree / NVQ4 or higher	Reference				
High PD use vs Low PD use					
Risk perception	-0.186	0.015	<0.001	0.83	(0.81, 0.86)
WHO-5	0.006	0.003	0.093	1.006	(0.99, 1.01)
Events past 12 months	0.027	0.005	<0.001	1.03	(1.02, 1.04)
Age	0.037	0.018	0.045	1.04	(1.001, 1.08)
Gender					
Female	Reference				
Male	-0.021	0.140	0.882	0.98	(0.75, 1.29)
Country					
Belgium	-1.943	0.216	<0.001	0.14	(0.09, 0.22)
Italy	-3.857	0.476	<0.001	0.02	(0.01, 0.05)
Netherlands	0.322	0.179	0.072	1.34	(0.97, 1.96)
Sweden	-1.912	0.241	<0.001	0.15	(0.09, 0.24)
UK	Reference				
Education					
Secondary school / key stage 3 or less	0.09	0.263	0.731	1.09	(0.65, 1.83)
GCSE / A-level / key stage 4	-0.143	0.161	0.374	0.87	(0.63, 1.20)
University degree / NVQ4 or higher	Reference				
Abbreviations: UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO – World Health Organisation					

Table 5.9: Results from risk perception and well-being logistic regression models at follow-up, adjusted for demographic characteristics

	Coefficient	S.E.	p	OR	(95% CI)
Moderate PD use vs Low PD use					
Risk perception	-0.112	0.021	<0.001	0.89	(0.86, 0.93)
WHO-5	0.006	0.007	0.409	1.01	(0.99, 1.02)
Events past 12 months	0.012	0.003	<0.001	1.01	(1.006, 1.02)
Age	0.02	0.038	0.602	1.02	(0.95, 1.10)
Gender					
Female	Reference				
Male	-0.842	0.311	0.007	0.43	(0.23, 0.79)
Country					
Belgium	0.006	0.517	0.990	1.01	(0.37, 2.77)
Italy	-0.429	0.517	0.407	0.65	(0.24, 1.79)
Netherlands	0.390	0.437	0.372	1.48	(0.63, 3.48)
Sweden	0.528	0.532	0.321	1.69	(0.60, 4.81)
UK	Reference				
Education					
Secondary school / key stage 3 or less	-0.688	0.573	0.230	0.50	(0.16, 1.55)
GCSE / A-level / key stage 4	0.231	0.321	0.471	1.26	(0.67, 2.37)
University degree / NVQ4 or higher	Reference				
High PD use vs Low PD use					
Risk perception	-0.095	0.035	0.007	0.91	(0.85, 0.97)
WHO-5	0.002	0.009	0.837	1.002	(0.98, 1.02)
Events past 12 months	0.045	0.009	<0.001	1.05	(1.03, 1.07)
Age	-0.053	0.047	0.261	0.95	(0.87, 1.04)
Gender					
Female	Reference				
Male	-0.623	0.350	0.075	0.57	(0.27, 1.06)
Country					
Belgium	-1.143	0.645	0.077	0.32	(0.09, 1.13)
Italy	-2.068	0.980	0.035	0.13	(0.02, 0.86)
Netherlands	1.074	0.496	0.030	2.93	(1.11, 7.74)
Sweden	-0.812	0.609	0.182	0.44	(0.13, 1.47)
UK	Reference				
Education					
Secondary school / key stage 3 or less	0.089	0.619	0.886	1.09	(0.33, 3.68)
GCSE / A-level / key stage 4	0.392	0.431	0.363	1.48	(0.64, 3.44)
University degree / NVQ4 or higher	Reference				
Abbreviations: UK – United Kingdom; GCSE – General Certificate of Secondary Education; NVQ – National Vocational Qualification; WHO – World Health Organisation					

5.3.7 Transitions in latent status membership

Table 5.10 displays the estimated transition probabilities, which show the probability of belonging to a particular class at follow-up conditional on membership status at baseline. The diagonal cells highlighted in bold reflect the probability of belonging to the same status at follow-up as at baseline. These probabilities show that participants had a likelihood of between 88.5% and 94.8% of belonging to the same status at follow-up, suggesting that polydrug use remained stable over the course of 12 months for the majority of this population. The *Low polydrug use* status had the highest probability of remaining stable, followed by the *High* then *Moderate polydrug use* statuses.

Table 5.10: Estimated transition probabilities between latent status at baseline (columns) and latent status at follow-up (rows)

	FU Low use	FU Moderate use	FU High use
BL Low use	0.948	0.050	0.002
BL Moderate use	0.040	0.885	0.075
BL High use	0.023	0.064	0.913

Probabilities of remaining in the same latent status at follow-up as at baseline highlighted in bold. Abbreviations: BL – baseline; FU – follow-up

The patterns of latent status membership over time are shown in Table 5.11. Consistent with estimated transition probabilities, only 7.46% of the sample belonged to a different status at follow-up than at baseline. Amongst those who did change status membership, the most prominent trend was an increase in polydrug use through transitioning from *Low* to *Moderate* or *Moderate* to *High polydrug use* statuses.

Table 5.11: Patterns of latent status membership at baseline and follow-up

	Status at baseline	Status at follow-up	%	(N)
Stayers (92.54%)	Low	Low	40.59	(1176)
	Moderate	Moderate	31.79	(921)
	High	High	20.16	(584)
Movers (7.46%) Increase (4.38%)	Moderate	High	2.14	(62)
	Low	Moderate	2.14	(62)
	Low	High	0.10	(3)
Decrease (3.08%)	Moderate	Low	1.42	(41)
	High	Moderate	1.21	(35)
	High	Low	0.45	(13)

5.3.8 Association between status transition, risk perception and demographic characteristics

The associations between mean baseline risk perception scores, demographic characteristics and either increasing or decreasing polydrug use status at follow-up are displayed in Table 5.12. After adjusting for all variables in the model, an increase in risk perception score was associated with significantly lower odds of either increasing or decreasing levels of polydrug use, compared to those whose status did not change at follow-up. When comparing those who increased their use to those who decreased their use, no significant difference with regard to risk perception was observed.

Table 5.12: Results from risk perception and demographic changes logistic regression models on increasing and decreasing latent status transitions

	B	S.E.	p	OR	(95% CI)
Increased use vs No change					
Risk perception at baseline	-0.050	0.017	0.003	0.95	(0.92, 0.98)
Difference in events	0.009	0.003	0.004	1.01	(1.003, 1.02)
WHO-5 at baseline	0.003	0.005	0.57	1.003	(0.99, 1.01)
Gender (male)	0.079	0.194	0.68	1.01	(0.74, 1.58)
Moved country	0.186	0.598	0.76	1.21	(0.37, 3.90)
Increased education	0.092	0.247	0.71	1.10	(0.68, 1.78)
Decreased use vs No change					
Risk perception at baseline	-0.062	0.020	0.002	0.94	(0.90, 0.98)
Difference in events	-0.014	0.005	0.008	0.98	(0.97, 0.99)
WHO-5 at baseline	0.003	0.006	0.57	1.003	(0.99, 1.02)
Gender (male)	-0.175	0.239	0.46	0.84	(0.53, 1.34)
Moved country	-0.703	0.479	0.14	0.50	(0.19, 1.27)
Increased education	-0.217	0.328	0.51	0.81	(0.42, 1.53)
Increased use vs Decreased use					
Risk perception at baseline	0.001	0.032	0.99	1.001	(0.94, 1.07)
Difference in events	0.028	0.010	0.004	1.03	(1.01, 1.05)
WHO-5 at baseline	-0.002	0.007	0.83	0.99	(0.98, 1.01)
Gender (male)	0.207	0.310	0.50	1.23	(0.67, 2.26)
Moved country	0.643	0.754	0.39	1.90	(0.43, 8.33)
Increased education	0.371	0.423	0.38	1.45	(0.63, 3.32)

OR – Odds ratio; 95% CI – Odds ratio 95% confidence interval

The only significant association with status transitions and demographic characteristics was found with the mean number of events attended in the past 12 months. Amongst those whose status membership changed at follow-up, an increase in the number of events attended over the course of the previous 12 months was significantly associated with higher odds of increasing polydrug use compared to those whose status membership remained stable. Conversely, a reduction in the number of events attended was associated with significantly lower odds of decreasing polydrug use compared to those whose use did not change. Thus, it follows that among those whose status membership changed over time (Table 5.12: Increased use vs decreased use), an increase in the number of events attended in the past 12 months was associated with increasing levels of polydrug use.

5.4 Discussion

5.4.1 Summary of results

This study investigated longitudinal profiles of polydrug use among young adults regularly engaging with the European nightlife scene, and the influence of risk perception, nightlife engagement and demographic traits on change in use at 12 month follow-up. As far as the author is aware, this is the first LTA conducted amongst a nightlife population. Three statuses of polydrug use were found at both baseline and follow-up: *Low polydrug use* (42.84% of the sample at baseline; 42.46% at follow-up); *Moderate polydrug use* (35.34%; 35.14%); and *High polydrug use* (21.82%; 22.40%). More extensive polydrug use as defined by status membership was associated with lower mean risk perception scores and more frequent attendance at electronic dance music events, while latent statuses also differed with respect to age, gender, country of residence, education and wellbeing.

The identified polydrug use statuses showed high stability over the course of 12 months, with the probability of belonging to the same status at baseline and follow-up being at least 0.885. Among the 7.46% whose status changed at follow-up, an increase was more likely than a decrease in polydrug use. Relative to those whose use did not change, both an increase and decrease in polydrug use was associated with lower mean baseline risk perception scores. Furthermore, increasing attendance at electronic dance music events at follow-up was associated with an increase in polydrug use amongst those whose use changed, while attending fewer events was associated with decreasing levels of use. No demographic characteristics were associated with transitions in drug use in either direction.

5.4.2 Polydrug use profiles at baseline and follow-up

Over 40% of the sample at both baseline and follow-up belonged to the *Low polydrug use* status, which was characterised by probabilities of almost zero for use of any drug other than alcohol, tobacco and cannabis. However, almost 60% belonged to a class defined by moderate or high levels of polydrug use, suggesting this is a common practice amongst young adults regularly engaging with the European nightlife scene. While similarly high probabilities were observed for the past 12 month use of alcohol, tobacco cannabis and ecstasy in both the *Moderate* and *High polydrug use* statuses, considerably higher probabilities of the use of wider stimulants (cocaine, amphetamines), hallucinogens (LSD, magic mushrooms, synthetic hallucinogens), ketamine and nitrous oxide were found amongst *High polydrug users*. Interestingly, all three groups had very low probabilities (>0.10) of endorsing past 12 month use of mephedrone, synthetic dissociatives, synthetic cannabinoids or heroin.

Figure 5.4 highlights the similarity in past 12 month endorsement probability profiles of the three statuses at baseline and follow-up. Indeed, the formal test of measurement invariance indicated that the 3 status latent model can be held equivalent over time. This is important conceptually (Lanza et al., 2010), as it suggests that the structure, and therefore interpretation, of latent subgroups of polydrug use among this population do not vary over the course of 12 months. The only notable difference between baseline and follow-up was observed in the *Moderate polydrug use* (status 2), with higher probabilities of endorsing past 12 month ketamine and cocaine use at follow-up than baseline, which might reflect the recent growth in the use of these drugs by European young adults (EMCDDA, 2019; Nationale Drug Monitor, 2019), and is a finding in this sample that is discussed in detail elsewhere (Grabski, Waldron, Freeman, Curran, & The ALAMA Consortium, *In preparation*).

5.4.2.1 Risk perception

At both baseline and follow-up, increasing levels of polydrug use were associated with lower mean risk perception scores. When adjusting for nightlife engagement and demographic traits, an increase in risk perception score was associated with significantly lower odds of being a member of either the *Moderate* or *High polydrug use* status than the *Low polydrug use* status at both baseline and follow-up. The magnitude of this effect was similar for the *Moderate* and *High polydrug use* statuses at both time points.

No previous study employing LTA in polydrug users has examined associations with risk perception, however these results are consistent with previous research in ecstasy users showing that perceiving use as very risky was associated with low rather than intermediate or high use (Smirnov et al., 2013). Furthermore, while the lowest mean risk perception scores were observed in the *High polydrug use* status, scores of 19.37 and 19.81 out of a possible 36 at baseline and follow-up respectively indicate at least some degree of attribution of risk to drug use amongst all participants in this sample. This supports findings from other studies that indicate a number of young adults are aware of the risks of their ecstasy use (Leung et al., 2010; Martins et al., 2011; Rigg & Lawental, 2018). Indeed, it may be that scales that ask individuals to attribute risk to a range of behaviours that vary in terms of the true risk they pose, such as that utilised by the EMSS, have a score that represents accurate perception of risk thus might be best conceptualised as measures of 'risk awareness'. In the current study, the score that might reflect an accurate awareness of risk based upon the behaviours contained within the scale is 21 (Dr Olivia Maynard & Professor Adam Winstock, *personal communication*). The latent status with a mean risk perception score closest to this value was the *Moderate polydrug use* (baseline 20.10; follow-up 20.54), closely followed by the *High polydrug use* status. The largest deviation from 21 was observed in the *Low polydrug use* status (baseline 24.19; follow-up 24.14), and was the only status to score above that representing an accurate awareness risk. As such, it might be argued that rather than the *Moderate* and *High polydrug use* groups being at higher risk due to lower risk perception, they have a close to accurate awareness of risk and the *Low polydrug use* status in fact over attribute risk to drug use. Future research might, therefore, best consider utilising risk perception scales to identify those who are risk aware and those who over and under attribute risk to behaviours, rather than as a linear measure of risk perception.

5.4.2.2 Past 12 month event attendance

An association between engagement with the nightlife scene and polydrug use was also observed at both time points. In line with previous studies investigating nightlife engagement amongst alcohol, ecstasy, and other illicit drug users (Leslie et al., 2015, 2016; Smirnov et al., 2013; Van Havere et al., 2011), groups defined by higher levels of polydrug use attended electronic music events with greater frequency on average in the past 12 months. Furthermore, when adjusting for risk perception and demographic characteristics, an increase in the number of events attended was associated with significantly higher odds

of membership of the *Moderate* and *High polydrug use* compared to the *Low polydrug use* status, except for the *Moderate polydrug use* at baseline which fell just short of statistical significance. This effect was more pronounced for *High polydrug users*, with larger adjusted odds ratios observed for this group. Taken together, these findings suggest that levels of nightlife engagement may be useful in identifying individuals who might be most at risk of harm associated with polydrug use.

5.4.2.3 Demographics

All omnibus tests of group differences in demographic characteristics were statistically significant, demonstrating good discriminant validity of the three class solution at baseline and follow-up. Regarding country level differences, similar patterns were observed as in Chapter 3, with the *Moderate* and *High polydrug use* groups dominated by participants living in the Netherlands or UK, while those resident in Belgium, Italy or Sweden were more likely to belong to the *Low polysubstance use* group at both time points. Members of the *Moderate* and *High polydrug use* groups had a higher mean age than those in the *Low polydrug use* group, although the largest difference was just less than one year. The most notable difference in terms of gender was that women were more likely to be members of *Moderate polydrug use* statuses at baseline and follow-up, while those who had completed university or an equivalent level of education similarly were more likely to be *Moderate polydrug users*.

Interestingly, higher wellbeing as indexed by mean WHO-5 scores were found in the *Moderate* followed by the *High* then *Low polydrug use* groups. As noted in Chapter 3, this inverse U-shape curve appears to go against findings suggesting polydrug use is associated with poorer mental health (e.g. Quek et al., 2013). It may be that members of *Low polydrug use* are less outgoing than those in the other two groups, which may in turn affect their wellbeing over and above drug use. Indeed, this may also be reflected in the less frequent event attendance observed in this group. However, adjusted odds ratios were only significant for the difference between *Moderate* and *Low polydrug use* at baseline. It should also be noted that the largest difference in mean WHO-5 scores was just over three points out of a possible 100, raising questions as to how meaningful these observed differences are.

5.4.3 Longitudinal transitions in polydrug use status

The most common polydrug use trajectory was to remain in the same status at 12 month follow-up as at baseline. Membership of the *Low polydrug use* class had the highest probability of remaining stable over 12 months (0.948), followed by the *High* (0.913) and *Moderate polydrug use* (0.885) statuses. Indeed, only 7.46% of the sample belonged to a different polydrug use status at follow-up. These findings are consistent with previous LTA studies that have shown polydrug use to remain stable over time in adolescents (Choi et al., 2018; Tomczyk et al., 2016) and young adults (Baggio, Studer, Deline, et al., 2014; Cho et al., 2015; Lanza et al., 2010; Merrin et al., 2018; Mistry et al., 2015). Important maturation milestones in early adulthood, such as getting married and having children, are thought to influence the natural cessation of recreational drug use during young adulthood (Ramo et al., 2011; Smirnov et al., 2013; von Sydow, Lieb, Pfister, Höfler, & Wittchen, 2002). The mean age of our sample was just under 24, thus it may be that the majority of participants were too young to have experienced milestones that may result in a natural reduction in drug use. Future studies into the transitions of polydrug use might, therefore, benefit from incorporating measures that capture life event experiences over the course of the study.

The observation that the *Low polydrug use* status had the highest stability probabilities somewhat conflicts with previous findings that have identified statuses characterised by the heaviest polydrug use patterns as the most stable (Lanza et al., 2010; Merrin et al., 2018). However, the *High polydrug use* status in this current study also had a very high probability of stability. This is an important finding, as it suggests that those who exhibit the riskiest polydrug use patterns are also amongst those for whom drug use may be most entrenched. As such, it seems reasonable to suggest that this is further evidence that *High polydrug users* should be a high priority target of intervention efforts.

Although the vast majority of the sample remained in the same polydrug use status over time, interesting transitions did occur. Again supporting findings from previous LTA studies (Cho et al., 2015; Merrin et al., 2018), the most common transition was an increase (*Low to Moderate or High; Moderate to High*) rather than a decrease (*High to Moderate or Low; Moderate to Low*). Given that the move from the *Moderate to High polydrug use* statuses not only represents a transition to potentially riskier drug use, but also to more stable patterns of use suggests that interventions designed to guard against increasing transitions would be of benefit to some in this population.

5.4.4 Differences between latent status ‘movers’ and ‘stayers’

5.4.4.1 Risk perception

Interesting differences were found between latent status ‘movers’ and ‘stayers’. Compared to individuals whose membership status had not changed at follow-up, an increase in risk perception score was associated with significantly lower odds of both increasing and decreasing polydrug use, after adjusting for event attendance and demographic characteristics. As such, increasing and decreasing levels of polydrug use were both associated with lower risk perception. Although no study has utilised LTA to investigate the association between polydrug use transitions and risk perception, the finding that an increase in polydrug use was associated with lower baseline risk perception is in accordance with previous studies in ecstasy users (Leung et al., 2010; Smirnov et al., 2013).

However, those who decreased their polydrug use in the present study also had lower average baseline risk perception scores than those who did not change, and did not differ from those who increased their use. This is seemingly at odds with findings of lower risk perception predicting increasing levels of use, and it is not clear why this is the case in this sample. It is possible that a decrease in polydrug use may be associated with other factors not included in these models, and which may also be associated with lower risk perception. One such factor might be drug use frequency, such that among this population people who used a fewer number of drugs at follow-up may have used others more frequently, which in turn may be associated with lower baseline risk perception. This, however, remains speculative at this stage.

Furthermore, the confidence intervals for the mean scores for those who increased (20.45; 95% CI 19.63-21.27) and decreased (20.01; 95% CI 19.00-21.03) both contain 21, the value that might indicate an accurate awareness of risk as discussed above, while for those whose use did not change (21.81; 95% CI 21.60-22.01) the lower bound confidence interval was above this value. This suggests that those who increased or decreased their use had more accurate awareness of risks than for those who did not change, who had an average score that indicates they might over attribute risk. Such an approach should be considered in future research, while also incorporating further measures, such as frequency and quantity of use, to fully elucidate the relationship between risk perception, risk awareness and polydrug use.

5.4.4.2 Past 12 month event attendance

A change in the number of electronic dance music events attended in the past 12 months at follow-up compared to baseline was found to be associated with changes in status membership, further highlighting the link between nightlife engagement and polydrug use (Leslie et al., 2015; Smirnov et al., 2013; Van Havere et al., 2011). Specifically, those who transitioned to increasing levels of polydrug use were more likely to have attended more events at follow-up than at baseline than those whose use did not change. Similarly, a reduction in polydrug use was associated with a reduction in the number of events attended at follow-up. This is an important finding for policy makers and those designing interventions, as event attendance appears to be a risk factor for higher levels of drug use. However, the design of this study does not allow an investigation into the extent to which increases or decreases in drug use were in the context of engaging with the nightlife scene, or reflect more general changes over the course of 12 months. Studies investigating short-term patterns of use over the course of a night out, such as the EMA study discussed in Chapter 1, would supplement these results and help further clarify the relationship between nightlife and drug use.

5.4.4.3 Demographics

None of the included demographic characteristics (baseline wellbeing; baseline gender; moving country at follow-up; increasing level of education at follow-up) were predictive of transitions in polydrug use status. The evidence from prior longitudinal studies is inconsistent, with some similarly finding no association between transitions and demographics (Lanza et al., 2010; Ramo et al., 2011), while others have found anxiety and depression to predict increasing transitions (Cho et al., 2015), and males to show more stability in high polydrug using classes (Choi et al., 2018). As such, future studies should continue to investigate the predictive ability of demographic characteristics on polydrug use transitions to identify those who might be at most risk of harmful use trajectories.

The results from logistic regression models comparing those who either increased or decreased their use with those who did not discussed here should, however, be interpreted with a degree of caution. As mentioned, the number of individuals who remained in the same status at follow-up (n=2681), was far greater than that of those who increased (n=127) or decreased (n=89), which may have had an effect on regression coefficient estimates. Furthermore, the 95% confidence intervals of significant adjusted odds ratios

were close to the null in all instances, indicating that the magnitude of the predictive effect of risk perception and event attendance might be quite small.

5.4.5 Strengths and limitations

This study has a number of strengths. Firstly, to the author's knowledge, this is the first study utilising LTA to examine transitions in polydrug use amongst young adults engaging with the European nightlife scene, and highlights the utility of this method amongst this population. Secondly, although the retention rate at follow-up was just over one third (36.01%), results from analyses of attrition indicate systematic bias with relation to drug use was unlikely to have been introduced to the sample by drop-out. Thirdly, the use of a 12 item scale asking about the risk of five licit and illicit substances is likely to capture risk perception in a more holistic manner than a single question as employed in previous studies (Leung et al., 2010; Smirnov et al., 2013).

However, the results presented in this chapter should be interpreted alongside limitations inherent within this study. Our 12 month follow-up period may have limited our ability to observe transitions, thus studies should consider longer assessment periods to assess whether similar rates of stability in the longer-term are observed in this population. Although attrition did not introduce bias into measures of drug use at follow-up, non-completers significantly differed from completers on a range of demographic characteristics. Also, the inevitably smaller sample at follow-up may have precluded the ability to uncover a longitudinal latent structure that contained more profiles and offered a more nuanced overview of polydrug use, such as the six class solution identified in Chapter 3. However, when exploring transitions, particularly in initial studies, it is of conceptual benefit to consider additive structures of polydrug use as demonstrated in this chapter. The influence of a wider range of demographic traits could also have been examined, such as sexual orientation which has received significant attention amongst nightlife populations (Halkitis, Green, & Mourgues, 2005; Halkitis, Mukherjee, et al., 2007; Halkitis & Palamar, 2008; Halkitis, Palamar, et al., 2007; Palamar, Mukherjee, & Halkitis, 2008).

There are also limitations with the risk perception scale that was used in the EMSS. This scale was developed for use in the European Schools Project on Alcohol and Drugs (ESPAD), and as such designed to capture risk perception in an adolescent sample. It was included in the EMSS due to members of the ALAMA-Consortium being involved in the ESPAD project and wishing for comparable data. However, on reflection, a scale more suitable to a young

adult sample with greater experience of drug use, such as that utilised by Morgan et al (2013), would have been more appropriate and might have more accurately captured risk perception and risk awareness in our sample. Finally, as discussed in Chapter 3, there are also limitations associated with the use of the WHO-5 in this sample.

5.4.6 Conclusions

In the first study utilising LTA in a population of young adults engaging with the European nightlife scene, *Low*, *Medium* and *High polydrug use* statuses were identified at baseline and 12 month follow-up. Membership of polydrug use status was found to be highly stable over the course of 12 months, with 92.54% of participants remaining in the same status at follow-up as at baseline. Of the 7.46% of the sample who did change status membership at follow-up, participants mostly transitioned upwards to increasing levels of polydrug use.

Both an increase and a decrease in polydrug use status at follow-up was associated with lower average risk perception scores measured at baseline. This warrants further research in order to inform interventions designed to raise awareness of the risks of polydrug use. Furthermore, increasing transitions of polydrug use were associated with more frequent attendance at electronic dance music events, while decreasing use was associated with less frequent attendance. These findings serve as important initial findings for policy makers and those designing interventions intended to prevent transitions to more risky patterns of drug use among Europeans engaging with the nightlife scene.

Chapter 6: General Discussion

The overall aim of this thesis was to gain insight into contemporary drug use patterns amongst young adults regularly engaging with the European nightlife scene.

In order to address this aim, I used data from the ALAMA-Nightlife study to answer the following questions:

1. Can the internet be successfully used to access a population of young adults regularly engaging with the European nightlife scene?
2. What are the different drug use profiles amongst this population, and what are their associations with potentially harmful alcohol and illicit drug use and demographic characteristics?
3. How does the adoption of harm reduction strategies relate to polydrug use, and to positive and negative experiences associated with drug use?
4. What are the transitions in polydrug use over 12 months, and how are risk perception, nightlife engagement and demographic characteristics associated with an increase, decrease or maintenance of use?

In this chapter I will bring together results from each study designed to answer these specific questions, and will discuss how findings help address the overall aim of this thesis. I will also discuss the wider implications of these findings, along with the methodological limitations and suggestions for future research arising from the work presented in this thesis.

6.1 Summary of findings

In Chapter 2, I compared EMSS survey respondents recruited online to an offline sample of young adults recruited at nightclubs and festivals with respect to their past 12 month use of five drugs (alcohol; cannabis; ecstasy/MDMA; cocaine; amphetamines) and their engagement with five nightlife venues (nightclubs; licensed festivals; illegal festivals; pubs/bars; house parties). A lower proportion of online participants used each drug in the past 12 months, although adjusted odds ratios suggest these differences were small. Online participants also used each drug less frequently than offline participants, although again effect estimates show these differences were small.

Similar patterns were found for nightlife engagement, in that fewer online participants attended each venue, with the exception of licensed festivals, and, apart from nightclubs, attended each less frequently on average in the past 12 months. Again, however, adjusted odds ratios and regression coefficients suggest that the majority of these differences could be considered small. Thus, findings from this Chapter (see also Waldron et al., 2020) indicate that internet recruitment can result in a sample of young adults in the nightlife scene that is broadly representative of those recruited at festivals and nightclubs. However, the lower rates and less frequent drug use observed suggests online recruitment may result in a sample that slightly underestimates true levels of drug use, particularly concerning illicit substances.

In Chapter 3, I used cross-sectional baseline data to conduct a LCA to identify different past 12 month drug use profiles. Six distinct classes of drug use were identified, which differed with respect to their past 12 month endorsement of 21 different licit and illicit drugs and were characterised as follows: *No illicit use* (16.81% of baseline sample); *Cannabis use only* (30.70%); *Low polydrug use* (16.05%); *Moderate polydrug use* (19.48%); *High polydrug use – hallucinogens/medication* (10.45%); and *High polydrug use – stimulants* (6.51%).

Differences in wellbeing between classes were observed, with membership of the *Cannabis use only*, *Moderate polydrug use* and *High polydrug use – hallucinogens/medication* classes associated with lower mean WHO-5 scores than the *No illicit use* class, while a higher mean score was found in the *Low polydrug use* class. Furthermore, all classes had higher mean AUDIT-C and DUDIT scores than the *No illicit use* class, suggesting that polydrug use was associated with higher rates of hazardous alcohol and illicit drug use.

In Chapter 4, I examined different patterns of harm reduction (HR) behaviours amongst polydrug users, and the associations between positive experiences and negative consequences of drug use. To this end, I conducted a further LCA on 30 protective behavioural strategies amongst members of the four polydrug using classes identified in Chapter 3. While strategies employed before, during and after use were widely adopted, five discrete patterns of endorsement were found: *Low HR before use* (10.94% of overall sample); *Moderate HR after use* (15.37%); *High HR with loading* (20.31%); *High HR no loading* (23.47%); *Extensive HR throughout* (29.91%).

Some evidence of a 'cautious' profile of drug use was found, with the highest proportion of Low polydrug users found in the *High HR no loading* classes, although conversely the largest

proportions of High polydrug users were found in the *High HR with loading* and *Extensive HR throughout*. In comparison to the *Low HR before use* class, all classes defined by increasing strategy endorsement were associated with significantly higher scores on the positive experiences subscale. Furthermore, both the *High no loading* and *Extensive HR throughout* classes also had significantly lower mean negative consequence subscale scores than the *Low HR before use* class, although differences were less pronounced.

In my final empirical study (Chapter 5), I conducted LTA with data from baseline and follow-up to assess the nature and stability of drug use trajectories over the course of 12 months. At both time points, three statuses of polydrug use were found (*Low polydrug use*; *Moderate polydrug use*; *High polydrug use*), with increasing levels of polydrug use associated with lower risk perception and attendance at more electronic dance music events. Membership of the three polydrug use statuses remained highly stable over time, with only 7.5% of the sample belonging to a different status at follow-up than at baseline. Amongst those whose status did change, the most common transition was an increase rather than a decrease in polydrug use. While no demographic differences were associated with status transitions, both an increase and a decrease in polydrug use at follow-up were associated with lower perceptions of risk at baseline. Furthermore, increasing levels of use were also associated with an increase in the number of events attended at follow-up compared to baseline, while a decrease in use was similarly associated with decreasing event attendance compared to those who did not transition status.

In summary, the research presented in this thesis provides evidence that there is considerable heterogeneity in drug use patterns amongst young adults regularly engaging with the European nightlife scene. Furthermore, findings suggest that polydrug users are to some degree aware of the risks that their use poses, and employ a range of protective behavioural strategies in differing ways to mitigate these risks. Evidence arising from this thesis further suggests that differing harm reduction patterns are themselves associated with more positive experiences and fewer negative consequences of drug use. I have also demonstrated that polydrug use profiles remain highly stable over the course of 12 months amongst this population. For those who do transition, lower baseline risk perception was found to be associated with both an increase and decrease in use, while an increase and decrease in event attendance was associated with an increase and decrease in polydrug use respectively.

6.2 Utility of the internet for researching drug use among those regularly engaging with the European nightlife scene

Ultimately, the success of the EMSS, and therefore the ALAMA-Nightlife project, hinged on the ability to recruit a sample of young European adults engaging with the nightlife scene using online methods. This turned out to be particularly the case given the far lower than anticipated proportion of offline participants recruited at nightclubs and festivals who later completed the full baseline EMSS, as discussed in Chapters 1 and 2.

In line with findings from a limited number of previous studies comparing online samples of drug users with probability samples (Barratt et al., 2017; Barratt & Lenton, 2015; Miller et al., 2010), in Chapter 2 I demonstrated that the internet can successfully recruit a sample of young European adults that is broadly representative of one known to regularly engage with the nightlife scene. To my knowledge, this is the first study to show this in a European nightlife population. However, small yet significant differences were found between the online and offline samples, consistent with previous studies that also conclude the internet can reach a sample broadly representative of the target population (Barratt et al., 2017; Barratt & Lenton, 2015; Miller et al., 2010).

The finding that the online sample reported lower rates of, and less frequent, drug use than the offline sample seems to contradict previous research that suggests samples recruited via the internet may over-report their drug use (Al-Salom & Miller, 2019; Barratt, Ferris, et al., 2015; Barratt et al., 2017; Wardell et al., 2014). As discussed in Chapter 2, it may be that the online sample had reservations about anonymity when disclosing illegal behaviours, while those in a club or festival environment may have felt less inhibited, possibly due to the influence of alcohol or other drugs, the party atmosphere, or a combination of the two.

However, this remains speculative at this stage, and a more substantive explanation might be that these differences are attributable to differing online recruitment methods between the studies cited here and the EMSS. For example, an online sample of individuals living in Australia, Switzerland or the USA were found to have higher proportions of lifetime and past 12 month cannabis use than probability samples from household surveys in each respective country (Barratt et al., 2017). However, online participants were completers of the GDS, which purposively recruits a drug using sample thus elevated levels of use are perhaps to be expected. Similarly, Australian ecstasy users recruited online were found to be more likely to report use of stimulants and hallucinogens than participants completing a

household probability survey, despite both samples being matched for frequency of ecstasy use (Barratt, Ferris, et al., 2015). As online participants were recruited through internet fora for people who used stimulants and hallucinogens, it is again unsurprising that more widespread drug use was observed in this group. However, Miller et al (2010) also recruited ecstasy users primarily through drug related internet fora and websites, and, although not matched for frequency of ecstasy use, found online participants to be less likely to report past 6 month use of alcohol, cannabis and cocaine than those completing a household probability survey. These disparate findings, along with the results reported in Chapter 2, show the value of corroborating patterns of drug use found in online samples with those utilising a variety of other recruitment methods.

As discussed in the General Introduction to this thesis, a number of young adults who engage with the nightlife scene do not use substances, and could be informative about reasons for cessation and potential initiation of use. As such, the online recruitment strategy of the EMSS avoided relying primarily on groups, fora and websites focussing on drug use in order to minimise the chance that this subgroup were missed from our sample. In Chapter 3, the finding of a substantial group of baseline EMSS completers who had very low probabilities of use of drugs other than alcohol or tobacco shows we were successful in this regard, at least with respect to illicit drugs. Conversely, fieldworkers at clubs and festivals introduced the offline questionnaire as 'a study about drug use and nightlife', which conceivably could have disproportionately discouraged those who do not use drugs from taking part. This may in part explain why I observed lower rates of use in the online sample in Chapter 2, and highlights the importance of appropriately designing internet-based and comparative offline recruitment strategies.

Beyond the lower overall rates of use observed in the online sample in Chapter 2, interesting between drug differences were also found. With respect to the proportions of past 12 month use, the difference for alcohol was non-significant at the Bonferroni corrected level when adjusting for demographic differences between the two samples. Differences between samples for the remaining four drugs remained significant, albeit with confidence intervals indicating true differences may be relatively small, suggesting the internet may be less successful at recruiting illicit than licit drug users. This is an avenue worthy of further research, using a wider range of drugs both licit (such as tobacco and prescription medication) and illicit (for example hallucinogens and NPS), to help ascertain the extent to which drug specific limitations to online recruitment exist.

Studies concluding fair representativeness of online samples, in line with Chapter 2, have also found similar but non-identical demographic characteristics across samples. In Chapter 2, online participants were found to be younger on average with a lower proportion of women than the offline sample. While studies generally converge on the finding that online participants are more likely to be male (Barratt et al., 2017; Barratt & Lenton, 2015; Miller et al., 2010; Miller & S nderlund, 2010), the association with age is less robust. For example, Barratt et al (2017) found that GDS respondents from Australia and Switzerland were younger on average than samples from respective national household surveys, while those from the USA had higher proportions belonging to older age groups. It is not unreasonable to suggest that samples recruited in different settings might also differ on a wider range of demographic traits than age and gender. Thus, in order to gain further insight into the strengths and limitations of the internet in recruiting nightlife populations, similar validation studies are now required in a variety of different locations, investigating a wider range of drugs and demographics.

Further to the preliminary evidence from Chapter 2 that a large, broadly representative nightlife population can be recruited online, research presented in this thesis shows the internet can also be successful at accessing a diverse sample within which nuanced patterns can be detected. Findings from Chapters 3 and 5 showed that distinct patterns of polydrug use existed within the EMSS sample, while findings from Chapter 4 showed discrete subgroups of harm reduction behaviours. Furthermore, the discriminant validity of each solution was confirmed in all three studies, with subgroups differing significantly on all tested demographic characteristics and indices of wellbeing, problematic alcohol and other drug use, nightlife engagement and risk perception.

That the internet can successfully recruit a representative sample, within which nuanced patterns of drug use and related behaviours can be found, is encouraging news for future research in among European nightlife populations. Given the dynamic nature of the European drug market, the close and frequent monitoring of emergent trends among those engaging with the nightlife scene is vital in order to appropriately respond to these changes. The internet has the potential to be an excellent tool with which to do so, given its ability to reach a large number of people very quickly at a fraction of the cost of more traditional recruitment methods (Miller & S nderlund, 2010). Research in this thesis shows that such samples lend themselves well to complex latent modelling techniques, which I believe to be amongst the most informative approaches to studying drug use profiles and

trajectories. Given this, and the limitations and cost inherent with offline recruitment, further validation studies of European nightlife samples are perhaps unnecessary, and should be reserved for populations recruited online yet to be shown to be representative. I would, therefore, strongly advocate more widespread use of the internet to regularly assess drug use among nightlife populations as an efficient approach to informing and updating education and harm reduction interventions in response to emergent trends.

6.3 Polydrug use profiles and trajectories

Three studies presented in this thesis employed latent variable mixture modelling techniques (LCA and LTA) to uncover cross-sectional and longitudinal subgroups of polydrug use among those regularly engaging with the European nightlife scene, based on the past 12 month use of 21 licit and illicit drugs.

6.3.1 Cross-sectional profiles

In line with the only previous LCA study among a European nightlife population of which I am aware (Hannemann et al., 2017), Chapter 3 uncovered discrete profiles of past 12 month polydrug use differentiated by patterns beyond simply an increase or decrease in the number of drugs used. Furthermore, these findings extend those by Hannemann and colleagues (2017) by considering a wider range of drugs in a much larger, multi-country sample, and strengthen the evidence that polydrug use among those regularly engaging with the European nightlife scene is a nuanced phenomenon.

In addition to four distinct classes of polydrug user, in Chapter 3 I found that 16.81% of the sample in fact had very low probabilities of use of any drug other than alcohol, while an additional 30.70% were only likely to have used alcohol, tobacco and cannabis. This supports previous findings of a large proportion of cannabis users only in Munich (Hannemann et al., 2017) and New York (F. Fernández-Calderón et al., 2018) and that of a substantial non illicit using group in São Paulo (Sanudo et al., 2015). Taken with the differing patterns of use amongst those identified as polydrug users discussed extensively in Chapter 3, these findings suggest that a 'one size fits all' approach to interventions intended to minimise harm may not be optimal, and support, for example, conclusions reached by Hannemann et al (2017) that focussing on the potential harms of alcohol or cannabis use may be sufficient for a substantial proportion of this population.

One common feature of all cross-sectional profiles elicited in Chapter 3 is the high probability of past 12 month alcohol use, with the probability of use at least 0.85 for all classes. Although the study conducted by Hannemann and colleagues (2017) did not include alcohol use as a latent class indicator, an association between increased levels of polydrug use and binge drinking has been found in a Brazilian nightlife population (Sanudo et al., 2015). However, no LCA study in nightlife populations has examined polydrug use and hazardous alcohol consumption as indexed by validated scales such as the AUDIT. In Chapter 3, I demonstrated that in comparison to the *No illicit use* class, membership of all five remaining classes defined by higher levels of illicit use was associated with increased AUDIT-C scores, echoing findings from a nationally representative UK household survey (Smith et al., 2011). However, while Smith et al (2011) found an additive three class model of polydrug use, with higher AUDIT scores found in classes defined by a greater degree of polydrug use, the more nuanced profiles I found in Chapter 3 suggest that the association between problematic alcohol use and polydrug use may also be more complex. Indeed, the *Moderate polydrug* and *Cannabis use* classes were those with the largest difference in AUDIT-C scores compared to the *No illicit use* class, suggesting there may be a subset of this population with limited polydrug use but for whom the risk of problematic alcohol use is particular high. However, the mean AUDIT-C score for the sample as a whole was 5.4, above the cut off indicating an increased risk of alcohol related harm (Bush et al., 1998). Furthermore, over 80% of the sample scored this cut-off or above. As such, these initial findings suggest that European nightlife populations would benefit from universal messages about the risks associated with heavy alcohol use.

A common feature of all four polydrug using classes reported in Chapter 3 was the high probability of ecstasy use (>0.85 for all). This supports evidence of the particular association between ecstasy use and engagement with the electronic dance music scene (Palamar, Acosta, Ompad, & Cleland, 2017; Ter Bogt & Engels, 2005; Van Havere et al., 2011; Winstock et al., 2001), and previous research finding ecstasy to be one of the most commonly used substances in the context of polydrug use in this population (Groves et al., 2009). Furthermore, a similar pattern was detected in a German nightlife population, with probabilities greater than 0.90 for past year ecstasy use in all three identified polydrug use classes (Hannemann et al., 2017). Given concerns about the rise in average MDMA content in ecstasy pills currently available on the European drug market (discussed in Chapter 1), continued messages about the increased risk of higher potency pills, particularly notifying

people about those tested as ‘super-strength’, is of paramount importance for those engaging with the nightlife scene.

However, that clear between-profile differences were found to exist highlights the need for tailoring interventions for specific groups. For instance, although the past 12 month prevalence of use of NPS in the EMSS baseline sample was lower than that of more ‘traditional’ drugs, a defining characteristic of the two *High polydrug use* classes over the rest was their moderate to high probability of use of synthetic hallucinogens, while the members of *High polydrug use – stimulants* also had high probabilities of endorsing use of 4FA.

This finding seems to converge with Hannemann and colleagues (2017), who used past 12 month of any NPS as an LCA indicator, with higher probabilities similarly observed in the class defined by the most extensive polydrug use. Research presented in Chapter 3 extends these findings among European nightlife populations, and replicates those in a sample from New York (F. Fernández-Calderón et al., 2018) that similarly showed polydrug use profiles to be associated with use of NPS that elicit similar effects as more traditional drugs whose use is a feature of said profile (hallucinogens and stimulants). While this suggests that polydrug users may seek NPS that have similar effects to more traditional drugs they use, further research is needed to ascertain whether this is in response to the sporadic unavailability of drugs they prefer or a desire to expand their drug use repertoire. If the latter, then the extent to which NPS are used in conjunction with other drugs also deserves assessment given the potential for exacerbating the risk of negative impacts on health (Moore et al., 2013; Palamar, Su, & Hoffman, 2016).

Another interesting finding from Chapter 3 was the moderate probabilities of use of benzodiazepines and, to a lesser extent, prescription opioids in the *High polydrug use – hallucinogens/medication* class, identifying a further subgroup potentially at elevated risk of drug related harm. Moderate to high probabilities of use of ‘medicines’ were observed among the most extensive polydrug use class in Munich (Hannemann et al., 2017), although it is not clear what medications this term encompasses in this study, while use of both prescription opioids and benzodiazepines has been found in the New York electronic dance music scene (Kurtz, Buttram, & Surratt, 2017; Palamar et al., 2018).

Beyond concerns about developing dependence on these substances (Kurtz et al., 2017), it is thought that in nightlife populations these drugs are commonly combined to come down

from, or enhance the effects of, other drugs, thus increasing the risk of toxic health effects and overdose (Jones et al., 2012; Palamar et al., 2018). Previous studies have shown that it is often stimulants that are complements to such medications (Kurtz et al., 2017; Palamar et al., 2018), while in our sample elevated probabilities for benzodiazepine and prescription opioids were associated with higher probabilities of hallucinogen use. While the design of the EMSS precludes any conclusions about the concurrent use of drugs, members of the *High polydrug use – hallucinogen/medication* class also had very high probabilities of ecstasy and cocaine use, thus medication use may have been similarly associated with stimulants for this group. Further research into the short-term patterns of drug use including medications is now required to better understand the impact of different combinations of drugs at different times.

The growth in the use of medications such as benzodiazepines and prescription opioids in the electronic dance music scene in New York has been attributed, in part, to the over-prescribing of these medications to the general population in the USA and their increased ‘at-home’ availability as a result (Palamar et al., 2018). Given that there have been growing concerns about over-prescribing in European countries such as the UK (Curtis et al., 2019; Levy, Mills, & Fawcett, 2019), the use of these substances by those regularly engaging with nightlife scene should now be routinely monitored to assess the impact of any observed changes in their use.

6.3.2 Longitudinal trajectories

The first LTA study investigating changes in drug use over time in a European nightlife population was presented in Chapter 5. Preliminary evidence that polydrug use profiles are highly stable over the course of 12 months was found, supporting findings from previous studies in non-nightlife specific young adult populations (Baggio, Studer, Mohler-Kuo, et al., 2014; Cho et al., 2015; Lanza et al., 2010; Merrin et al., 2018; Mistry et al., 2015). This is an important finding, particularly given the associations between polydrug use, wellbeing and hazardous alcohol and drug use found in Chapter 3, as this indicates that problematic use may be similarly stable.

Of the small percentage (7.46%) of EMSS respondents whose polydrug use status changed at follow-up, an increase was more likely than a decrease in use. No demographic characteristics were associated with transitions in either direction in our study. However, traits not included in my analyses, such as sexual orientation or urbanicity, might be

associated with polydrug use transitions (e.g. Palamar et al., 2008). As such, future studies into drug use trajectories among those regularly engaging with the nightlife scene should examine relationships with a variety of other demographic and social characteristics, to help identify groups of individuals who might have a greater propensity to increase their levels of polydrug use.

One reason for the low rates of movement I observed between polydrug use statuses might be down to the relatively short 12 month follow-up period of the EMSS. Although studies have demonstrated similar stability over longer periods of time, previous findings demonstrate the utility of longer follow-up periods with multiple assessments of drug use. For example, Mistry and colleagues (2015) followed a sample of Canadian adolescents into early adulthood with six assessments over ten years, and found that the probability of remaining in the same status from one wave to the next ranged from 0.58 to 0.94. While this demonstrates high overall stability in drug use, interestingly approximately half of the sample transitioned at least once over the course of the study, more often to statuses defined by higher rather than lower levels of use. Thus, when considering the notion of 'stability' of drug use over longer periods of time a different picture might emerge than when assessing status membership from one assessment to another. As such, longer-term longitudinal studies with multiple assessments of polydrug use among those regularly attending European nightlife would be vital additions to the existing literature. Furthermore, such studies might better highlight the influence of developmental milestones on natural courses of drug use amongst this population that, as discussed in Chapter 5, shorter term studies such as the EMSS may be unable to do.

Further to the 12 month stability of polydrug use status, in Chapter 5 I demonstrated that the latent structure used to model polydrug use also remained consistent over time. Indeed, the only subtle differences were the higher probabilities of ketamine and cocaine use at follow-up amongst the *Moderate polydrug use* status, reflecting an increase in use of these substances amongst the EMSS sample as a whole as discussed elsewhere (Grabski et al., *In preparation*). This suggests that the use of some drugs is robustly associated with the use of others over time, and is an important finding for tailoring consistent approaches to harm reduction. However, as the same latent class indicators are required at each time point, LTA does not provide scope to include additional drugs at different points in time. Therefore, this method cannot identify drugs that might emerge between assessments, nor how they might influence profiles of drug use. As such, regular cross-sectional studies

should be conducted to complement long term longitudinal assessments to monitor the emergence of new drugs of use among those engaging with the European nightlife scene.

Another benefit of using both cross-sectional and longitudinal methods is demonstrated by the difference in the latent structures of polydrug use between Chapters 3 and 5. In Chapter 3, I chose a six class solution with profiles differentiated by more nuanced patterns than simply an increase or decrease in the number of drugs used. However, in Chapter 5, an additive, three class solution was deemed the most appropriate. This suggests, therefore, that the common issue of attrition in longitudinal studies may have resulted in a reduction in statistical power, meaning more complex profiles may not have been able to be detected in the smaller number of follow-up completers. However, when examining transitions in drug use trajectories, assessing initial associations between simple increases and decreases is of conceptual benefit and utility in identifying risk factors for progressing to more risky use. As such, for longitudinal studies, conceptualising polydrug use as additive may be more informative, particularly given the current paucity of research among those engaging with the European nightlife scene. Conversely, Chapter 3 demonstrates that considering polydrug use as a nuanced phenomenon uncovers important sub-group differences. Thus, cross-sectional samples with large numbers (for which the internet is a useful tool) with sufficient statistical power to detect refined patterns of drug use continue to be of high importance.

6.3.3 Risk perception and harm reduction

Research presented in Chapter 5 demonstrated that among EMSS participants, an increase in polydrug use was associated with a lower mean risk perception score compared to no change. This intuitive finding is the first of its kind using latent statuses to model polydrug use in this population, and is consistent with results in ecstasy users showing heavier use to be associated with lower perceptions of risk of harm (Smirnov et al., 2013). However, that higher risk perception scores were associated with both an increase and a decrease in polydrug use relative to no change over 12 months is somewhat less intuitive. As mentioned in Chapter 5, it might be that amongst our sample a reduction in the overall number of drugs coincided with an increase in factors that might be associated with lower risk perception, such as increased frequency. This, however, is speculative at this stage and future studies should now examine the relationship between risk perception and drug use behaviours beyond past 12 month use.

While increasing polydrug use was associated with lower risk perception scores, the mean score of the *High polydrug use* group was almost 20 out of a possible 36. The scale used in the EMSS to index perceptions of risk was derived from the ESPAD project, which traditionally examines the scores associated with specific drugs rather than summing all items to form an overall score (e.g. Andreas, 2019; Piontek, Kraus, Bjarnason, Demetrovics, & Ramstedt, 2013). Although summing all items to capture risk associated with multiple substances was deemed an appropriate use of this scale (Dr Sabrina Molinaro, *personal communication*), it is the first time it has been used this way and thus there is no established indication of a threshold of 'risk awareness'. However, I would suggest that a score of approximately 55% (i.e. 20/36) indicates at least some awareness of the risks associated with drug use, even amongst those exhibiting the heaviest use patterns. Indeed, as discussed in Chapter 5, the most appropriate use of scales such as that used in the EMSS might be to identify those who show accurate risk awareness and those who under or over attribute risk to drug use behaviours. Taking this approach, both the *Moderate* and *High polydrug use* in fact demonstrated close to accurate awareness of risk, while the *Low polydrug use* status had a mean score suggesting an over attribution of risk.

Although not specifically tested in this thesis, it may be that the awareness of the risks of drug use drives people to adopt a range of protective behaviours in mitigation, which might explain the widespread endorsement of harm reduction strategies shown in Chapter 4. Furthermore, findings from my LCA on harm reduction behaviours revealed that the adoption of strategies clustered together in a discrete fashion. That differences were mainly observed in strategies employed before or after use is important in showing the need to consider harm reduction in a wider context than focussing solely on behaviours that occur in the moment of drug use.

Given that the sample in Chapter 4 was restricted to polydrug users identified in Chapter 3, it is unsurprising that avoiding combining drugs had amongst the lowest probabilities of endorsement across all five harm reduction profiles. Supporting previous results from a smaller survey in Spain (F. Fernández-Calderón et al., 2014), this finding suggests that as well as use of multiple substances over the course of 12 months, it might indeed be appropriate to consider polydrug use in terms of concurrent use within European nightlife populations. This is particularly noteworthy given concerns about elevated risk of harm as a result of the different potential interactions between drugs (Groß et al., 2009; Quek et al., 2013; Smith et al., 2011).

With regard to the relationship between harm reduction and polydrug use, patterns of drug use were found to relate to harm reduction profiles in differing ways. In a recent study (Fernández-Calderón et al., 2019) the use of individual substances was associated with differing odds of adopting six strategies the authors conceptually related to dosing. However, considering individual drugs and strategies is limited in that it does not take into account the way that these behaviours cluster together, particularly amongst a polydrug using sample.

Research presented in Chapter 4, therefore, extends these findings by providing the first empirical study to use LCA to elicit profiles of harm reduction and their associations with different polydrug use profiles. That LCA elicited five distinct harm reduction profiles which differed in their polydrug use validates the use of this method to consider harm reduction as an overall behaviour within which differing subgroups exist, as opposed to examining a narrow selection of individual strategies. Previous studies that categorise high and low polydrug users have shown evidence of a 'cautious' profile in that the adoption of a greater number of harm reduction strategies was associated with lower levels of drug use (F. Fernández-Calderón et al., 2014; Vera et al., 2018). Some evidence of this was found in Chapter 4, with over 80% of members of the *High HR no loading* class identified as belonging to the *Low or Moderate polydrug use* classes. However, this was not a universal finding, with both the *High HR with loading* and *Extensive HR throughout* classes containing substantial proportions of members of either the High polydrug using classes. Interestingly, the strategies that most differentiated these two harm reduction classes from the *High HR no loading* were pre- and post-loading, suggesting that the adoption of these might be particularly associated with more extensive polydrug use.

A further notable contribution of Chapter 4 to the existing literature is the creation, using exploratory factor analysis, of novel subscales to capture the extent to which participants experienced a range of negative consequences and positive experiences following drug use. Two previous studies have found the adoption of individual harm reduction strategies to be associated with a modest reduction in the odds of experiencing negative outcomes, based on binary 12 month measures of experiences (Fernández-Calderón et al., 2019; Vidal Gine et al., 2016). Using the negative consequence subscale, which is based on a measure of frequency of experience and thus likely to be more sensitive, I found some evidence to suggest that more extensive harm reduction adoption is associated with fewer negative experiences. However, interesting differences existed between profiles suggesting this

relationship may be somewhat more complex, and further demonstrating the value of determining subgroups of harm reduction behaviours. For example, that no difference in negative consequence subscale score were observed in the *High HR with loading* class suggests that pre- and post-loading might only be effective when used in conjunction with other strategies, such as avoiding combining drugs. Given that the highest, albeit still modest, probabilities of avoiding combining were observed in the two classes with the lowest negative consequence score (*Extensive HR throughout; High HR no loading*) indeed suggests that this strategy may be one which should be heavily promoted in nightlife populations. Given the cross-sectional nature of this study, such conclusions remain speculative and prospective studies are now required to test whether different profiles are indeed predictive of the likelihood of experiencing negative consequences.

The creation of a positive experiences subscale is both a new addition to the evidence-base and, I believe, an important acknowledgement that the majority of people use drugs for their perceived benefits. This is lacking from most research which often focuses only on drug harms. That all classes defined by more extensive strategy adoption than the *Low HR before use* had higher mean positive experience subscale scores should, perhaps above all, be an encouraging finding for those designing harm reduction interventions, as messages that both reduce harm and increase enjoyment seem likely to be those that will be most heard. As such, I would argue that future empirical research into harm reduction in the nightlife scene should also examine the associations with positive experiences to further aid the design of salient interventions. Indeed, differences for positive experiences were more pronounced than for negative consequences in Chapter 4. It might, therefore, be time to think about shifting away from ‘harm reduction’, that is away from the sole focus on the mitigation of negative outcomes, to one that incorporates the assessment of the positive effects people seek from drugs. This approach has been advocated elsewhere, notably by the Global Drug Survey’s High-Way Code (GDS, 2014), but to date seems to have been largely ignored in empirical studies, which I hope research presented here begins to address.

6.3.4 Nightlife engagement and polydrug use

Arguably the most robust finding throughout the Chapters in this thesis is the association observed between polydrug use and engagement with the electronic dance music scene. In Chapter 2, down-weighting offline participants who attended more events in the past 12 months attenuated all estimates of past 12 month drug use and drug use frequency, when

compared to unweighted estimates. Interestingly, this effect was most pronounced for ecstasy, cocaine and amphetamines, indicating that frequency of attendance might be most associated with use of such 'club drugs', more so than for substances such as alcohol and tobacco.

In Chapters 3 and 5, cross-sectional associations between nightlife engagement and latent sub-groups of polydrug use were observed. In the additive model employed in Chapter 5, at both baseline and follow-up, classes defined by more extensive polydrug use attended more events on average in the past 12 months. At both assessments, the difference between the *High* and *Moderate polydrug use* classes was far more pronounced than that between the *Moderate* and *Low polydrug use* groups. These findings are consistent with previous evidence that more frequent engagement with the nightlife scene, and electronic dance music in particular, is associated with elevated rates of drug use (Hunt et al., 2009; Leslie et al., 2015; Sanudo et al., 2015; Smirnov et al., 2013; Van Havere et al., 2011). Interestingly, in Chapter 3, which adopted a more nuanced model of polydrug use, the *High polydrug use – hallucinogens/medication* class attended substantially more events on average than all five remaining classes. The highest mean DUDIT score was also observed in this class, suggesting those who engage most frequently with the European dance music scene are more likely to endorse a past 12 month drug use repertoire associated with an elevated risk of problematic use. These findings entrench the notion that nightlife engagement can serve as a robust and easy to quantify indicator (in this case, simply the number of events attended in the past 12 months) of those with potentially elevated risk of increased drug use and drug related harm. Furthermore, that my findings converge on those employing more widely adopted methods than LCA further highlights the validity of this approach to identify sub-groups in nightlife populations.

In an important extension of these cross-sectional results, preliminary findings of longitudinal associations between engagement with the European nightlife scene and polydrug use were presented in Chapter 5. Specifically, both an increase and decrease in polydrug use at follow-up compared to baseline were associated with a respective increase or decrease in the average number of events attended in the past 12 months. While this is an important finding, I think that efforts to reduce problematic use by suggesting people modify how often they go out are unlikely to be successful. As such, nightlife engagement might still be best served as a way of identifying those who might benefit from

interventions aimed to promote, for example, use in moderation and avoiding combining substances.

6.4 Limitations

Despite the novel contributions that the research presented in this thesis makes to the literature, there are a number of limitations. There are also some things which, given the opportunity, I might do differently. Perhaps the most important consideration when interpreting the results in each Chapter is that the EMSS sample was restricted to young adults engaging with the electronic dance music scene in five European countries. It is known that drug use varies by music genre (e.g. Van Havere et al., 2011) and by country (EMCDDA, 2019), thus findings cannot be said to be representative of other nightlife scenes or of those in other countries. Furthermore, as demonstrated in Chapter 2, our online recruitment method may have slightly under-sampled heavier drug users. However, I would argue that it is more favourable to make inferences from a more 'conservative' sample than one in which drug use is over estimated, particularly in investigations providing preliminary evidence.

There are also limitations inherent with the EMSS study design. As discussed in Chapter 5, a 12 month follow-up period is relatively short and longer term assessment of drug use trajectories potentially incorporating times of major life changes might be more revealing.

High rates of attrition between baseline and follow-up were also observed, and while this did not seem to bias our sample with respect to drug use, it may have reduced my ability to detect more subtle longitudinal patterns. No effort was made to keep in touch with participants during the time between baseline and follow-up, and having done so may have not only served as a reminder of the study but also lead participants to feel more invested and thus willing to complete the follow-up survey. Furthermore, the only contact information we collected were email addresses, and having another way to contact those who did not respond to emails may have encouraged greater follow-up participation.

Arguably the most notable limitation with regard to study design, and frankly something that did not work as intended, was our offline recruitment. Chapter 1 highlighted that only 4.4% (n=352) of the baseline sample were recruited offline, far short of our intended target of 25%. This may in part be due to the difficulties we faced in agreeing access to clubs and

festivals, but it is perhaps more likely that people were unwilling to fill in a survey at a later date, or indeed forgot about it. While all was not lost in that we collected sufficient data from the offline questionnaires to enable sampling comparisons, efforts may have been better directed in encouraging people to complete the full survey in-situ at clubs or festivals, for example using tablets or smartphones.

Furthermore, a small number of items, such as indices of anxiety and depression (GAD-2 and PHQ-2), were added to the follow-up survey that were not included in the baseline survey, thus temporal associations with these variables could not be assessed.

Furthermore, the use of additional drugs (benzo fury; Ritalin; salvia divinorum; fentanyl) was assessed at follow-up and not baseline, thus were not included in models of drug use profiles and trajectories.

There are also potential limitations arising from the way in which we measured drug use. Perhaps most pertinent of these was the assessment of frequency of use, which used seven irregularly spaced frequency categories. As a result, latent class models attempting to account for frequency categories failed to converge on trustworthy solutions due to computational complexity and interpretation of mean differences were not possible. Future studies should consider alternative assessments of frequency of use, such as number of days used in the past year. The EMSS only asked about lifetime and past 12 month drug use, and not the short term patterns of use which are likely to be highly relevant when assessing drug use in the nightlife scene. The EMA study described in Chapter 1 was designed to complement the EMSS in this regard. However, that these data were not available meant that, as discussed throughout this thesis, I could not confirm whether polydrug use was in fact concurrent, although the low probabilities of avoiding combining drugs observed in Chapter 4 suggests it may be appropriate to consider that, at least in part, it was. We also relied upon self-report of drug use, which may be susceptible to recall bias. Furthermore, it is known that drugs available on the European drug market are sometimes adulterated with NPS and other substances (Brunt, 2017; Brunt et al., 2017), which clearly self-report cannot assess. Finally, quantity of use of each drug was not assessed, and while this is a difficult task given the many different available forms of drugs, it is an important limitation when assessing patterns of drug use.

6.5 Directions for future research

Despite the limitations discussed above, the novel findings presented in this thesis give rise to areas that should now be considered in future research.

While the internet offers a powerful tool to recruit typically hard to reach populations, studies using online methods in nightlife populations should consider offline methods to assess the representativeness of their sample. While findings from Chapter 2 suggest the internet can recruit a representative sample, observed differences and those found in other populations (Barratt et al., 2017; Barratt & Lenton, 2015; Miller et al., 2010) highlight the utility of validating samples recruited online whose study population has yet to be validated against those recruited using offline methods.

Given the success of LCA in revealing distinct subgroups of polydrug users demonstrated in this thesis, I would argue that this hereto underused approach provides the most holistic way of considering drug use, and should now be the method of choice when attempting to model polydrug use among those regularly engaging with the nightlife scene. Further LCA studies should now be conducted on large, multi-site European nightlife populations to see if the class structure I identified in Chapter 3 can be replicated, or whether further subgroups of polydrug user are identified.

Furthermore, latent indicators should be extended from past 12 month use to consider other behaviours, such as frequency and quantity of use. However, categorical or continuous indicator variables increase the complexity of models that can lead to computational issues and failures to find a solution (Muthén & Muthén, 2018). As such, consideration needs to be given to the balance between the complexity of indicator variables and including as many drugs in the model as possible to maintain a holistic view of polydrug use. However, as mentioned in Chapter 3, the use of binary 12 month indicator variables is likely to miss the finer complexities of drug use patterns, particularly concerning frequency of use. As such, following completion of this PhD, I plan to collapse the drug use frequency variables into 'never used', 'less than monthly use' and 'monthly use' and use these as latent class indicators in a further LCA, perhaps containing fewer drugs if necessary to mitigate against computational failure. These results will then be compared to findings presented here based upon 12 months use to investigate whether different profiles of use emerge when examining more frequent patterns of use.

Given that Chapter 5 presents the first investigation into polydrug use trajectories among those regularly attending the European nightlife scene, future studies should attempt to replicate these findings to provide a clearer picture of the stability of polydrug use over time. Studies should also incorporate additional measures and demographic characteristics to identify those most at risk of progressing to heavier and potentially problematic use. Moreover, longitudinal studies should now consider multiple assessments over a longer duration than 12 months. Indeed, in order to address this, I helped to successfully secure funding from the UK Department of Health for an extension to the EMSS in the UK in which we plan to contact participants for a third assessment in summer 2020.

With regards to the longitudinal associations between trajectories of drug use and risk perception, the seemingly inconsistent finding that lower risk perception was associated with both an increase and decrease in drug use again requires attempts at replication. Further variables that might be both associated with drug use and risk perception should also now be investigated.

Future research into risk perception might also consider whether scales that ask participants to rate the risk of behaviours that range in terms of the true levels of risk they pose, such as that used in the EMSS, actually measure risk perception or risk awareness. As discussed in Chapter 5, a score of approximately 21 on the ESPAD risk perception scale utilised in the EMSS represents an accurate awareness of the true levels of risk posed by the behaviours on this scale (Dr Olivia Maynard & Professor Adam Winstock, *personal communication*). Thus, rather than summing items on such scales to create a score of 'risk perception', it might be more appropriate and informative to identify the score that indicates 'accurate risk awareness', and examining the sample accordingly, for example by splitting into 'risk aware', 'risk unaware' and 'risk overly aware' groups.

Chapter 4 highlighted the benefit of not only considering polydrug use in a holistic manner, but similarly with doing so for drug related behaviours such as harm reduction. While there is now growing evidence that young adults in the European nightlife scene attempt to mitigate against drug related risk through the adoption of harm reduction strategies, there is scant evidence showing the extent to which these behaviours actually protect against harm. Studies such as those I conducted in Chapter 4 should now be repeated in different nightlife settings with different strategies. Furthermore, studies should consider utilising indices of negative consequence while also incorporating positive experiences with scales

such as the negative consequence and positive experience subscales from Chapter 4, as these provide an overall picture of experiences beyond single, binary measures.

Studies should also now include measures of positive experiences when assessing the role of harm reduction among nightlife populations. Findings in Chapter 4 indeed showed the effect associated with more extensive harm reduction adoption was more pronounced for positive than negative experiences. As such, future studies investigating the effectiveness of harm reduction strategies should also look at positive as well as negative experiences, as it may be that behaviours intended to mitigate harm are in fact more beneficial at promoting a more enjoyable drug use experience. This in turn can inform policy interventions, as the inclusion of positive experiences might mean they gain more credibility among the target population.

Pre- and post-loading were emphasised in Chapter 4 as strategies that might be of specific interest for future research. Investigations into what people use to pre- and post-load, whether this differs by harm reduction or polydrug use profile, and whether some might be more effective than others are all areas worthy of further research.

Future research into harm reduction should also consider the grouping strategies into before, during and after use as in Chapter 4. The adoption of this approach would provide a framework for a more widespread assessment of the acceptability of harm reduction strategies to users. Where acceptable, such an approach would be informative for efforts promoting effective strategies. For example, before use strategies might be promoted on event and ticket sale websites, during use strategies on posters at venues and after use on flyers handed out when leaving venues.

Finally, while the novel findings using LCA and LTA in this thesis need replication before definitive conclusions can be drawn, other methods would be an important complement to these and, hopefully, future studies using profile modelling techniques. As discussed above, the design of the EMSS cannot account for the short term patterns of drug use in nightlife, which is an important limitation. As outlined in Chapter 1, a further component of the ALAMA-Nightlife project was an Ecological Momentary Assessment (EMA) to assess patterns of drug use over the course of a night out, and short term predictors and consequences of use, which was designed to complement the longer term patterns found in the EMSS. Unfortunately, these data are still being processed thus were unavailable for use in this PhD. It will be of particular interest to see how patterns of polydrug use over the

course of 12 months presented in this thesis map onto patterns of simultaneous polydrug use revealed by the EMA, and such a mixed methods approach should be considered when researching drug use in nightlife populations.

6.6 Concluding remarks

Returning to the overall aim of this thesis, what can now be said about contemporary drug use patterns among young adults regularly engaging with the European nightlife scene? That alcohol was the dominant drug is an important finding given it is thought to be amongst the most potentially harmful (e.g. Nutt, King, & Phillips, 2010). While some appear not to use illicit substances beyond cannabis, if at all, polydrug use is a real and nuanced phenomenon for a substantial proportion. Furthermore, patterns of polydrug use appear to be heterogeneous and not simply additive, with those that are more extensive potentially associated with problematic alcohol and other drug use. However, it seems many are aware of the potential for drug related harm, and adopt a variety of harm reduction strategies in mitigation. The adoption of such strategies also appears to cluster in nuanced patterns, with those characterised by a higher level of adoption associated with a more positive and somewhat less negative experience of drug use. Furthermore, patterns of polydrug use appear highly stable over the course of 12 months. Given the novel nature of these findings, efforts should be made to replicate them in order to strengthen our understanding of drug use among those engaging with European nightlife scene.

6.7 Reflections on my PhD

As mentioned in the introduction, the UK team at UCL were work-package leaders of the EMSS and thus had overall responsibility for its implementation, launch and monitoring. My role within the UK team was, along with my colleague (Dr Meryem Grabski), essentially to project manage and coordinate each required stage, from finalising survey content, design, translation, online development, recruitment advertising, reporting and data cleaning and distribution, along with resolving myriad glitches and queries such a large scale collaboration inevitably entails.

Managing this workload, along with the expectations of over 20 different collaborators, to ensure we kept to the project's strict timetable while also staying on top of the requirements for my PhD was, at times, quite stressful. One of main reasons I feel that I was able to successfully negotiate these demands was that I quickly developed constructive, supportive and honest working relationships, many of which I hope will continue to be fruitful for years to come. Indeed, one of the most enjoyable aspects of my PhD was the opportunity to work on a multi-country collaboration with researchers from a wide variety of backgrounds. At a time when Brexit became a horrifying fact, feeling part of a European team brought home to me just how vital it is that we continue to foster these relationships, especially when malevolent egocentrism seems sadly to be on the rise.

As I was approaching the end of my studies, the world was hit by the coronavirus/Covid-19 pandemic and I am now finalising my thesis with the world on pause. Writing up research on drug use in the nightlife scene feels somewhat incongruous with social lockdown, given that going to clubs, pubs and festivals currently feels like a very distant memory. It is clear that this pandemic will have a major impact across society that will surely be felt by the nightlife scene, both in the short and long term. During my PhD, I helped secure funding for an extension to the EMSS in the UK, and we have included a module on the immediate impact of the pandemic and lockdown on drug use and nightlife engagement in the UK, which we are planning to launch as I write this. What the long-term repercussions might be remain to be seen, but I hope my suggestions for future research are not in vain, and that there is a vibrant nightlife scene to return to once the world presses play again.

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Appendices

Appendix 1 – EMSS baseline items

Demographics 1

1. Where did you hear about this survey?

- Online (1) / At a club (2) / At a festival (3) / Word of mouth (4)

<if Online (1)>

1.i Which website?

- Facebook (1) / Instagram (2) / Other *<if selected>* Please specify *<free text input>*

<if either at a club (2) or at a festival (3)>

1.ii Did a researcher give you a code to enter?

- Yes, and I still have it (1) / Yes, but I lost it (2) / No (3)

2. How old are you? years

3. What is your gender?

- Male (1) / Female (2) / Other (3)

4. Which country do you currently live in?

- UK (1) / Netherlands (2) / Belgium (3) / Sweden (4) / Italy (5) / Other (6)

5. What is your area code, i.e. the first 3 or 4 characters of your postcode? For example, if your postcode is WC1E 7HB enter 'WC1E'. This question is optional

- *Free text input*

Nightlife

6. How many times did you attend a dance/ electronic music event in the last 12 months?

<integer input>

7. On average, how often are the following genres of music played at dance/electronic music events you attend? If you have not heard of a certain music genre, please still respond by using the slider to select 'Never'

<Sliders ranging from "Never" to "All the time">

- House / Dubstep / Hard dance / Hardcore / Gabba / Techno / Trance / Goa-trance / Psy-trance / Drum 'n' bass / Jungle / Hip hop / R 'n' B / Reggae / Dancehall / Ragga / Ska / Electro / IDM / Experimental / New wave / Disco / Other

8. How important (**for you**) are the following reasons to go to a dance/ electronic music event?

<Not important (0) / Not very important (1) / Slightly important (2) / very important (3)>

- To dance / My friends are going / To meet new people / To look for sex / To look for a partner / To escape my daily life / To take drugs / To drink alcohol / To have fun / To listen to music / To explore my mind / To seek excitement / To cope with my problems / To open up to my friends / To see a particular artist or event

9.i Which of the following events or venues have you ever attended during your lifetime?

<radio buttons of following events/venues:>

- Nightclubs (1) / Licensed: festivals/outdoor parties/raves (2) / Illegal: festivals/outdoor parties/raves (2) / Pubs/bars (4) / House party/party at a friend's house (5)

<9.ii – 9.v asked for each event or venue ever attended>

9.ii How old were you when you first attended this event or venue?

- <integer input>

9.iii How often did you attend this event or venue in the last 12 months?

- Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1) / Not in the last 12 months (0)
<if select not in last 12 months, ask 9.iii.a, otherwise move to 9.iv>

9.iii.a How old were you when you last attended this event or venue?

- <integer input>

9.iv What age did you attend this event or venue most regularly?

- Age: <integer input> years to <integer input> years

9.v During this period of your life, how frequently did you attend this event or venue?

- Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1)

10. How many of your friends go to dance/ electronic music events at least 6 times in the last 12 months?

- None (0) / Some (1) / Many (2) / Most (3) / All (4)

11. Where do you get your information about dance/electronic music events that you attend? Please tick all that apply.

- Resident Advisor (1) / Facebook (2) / Twitter (3) / Word of mouth (4) / Friends (5) / Email lists or online newsletters (6) / Offline advertising (e.g. posters, flyers etc) (7) / Pirate or online radio stations (8) / Other websites (9) / Other (10)

Drug use

12.i. Have you used any of the following drugs in your lifetime? (yes/no)

- Alcohol (1) / Cannabis (2) / Synthetic cannabinoids (e.g. 'Spice') (3) / Benzodiazepines (e.g. Valium) (4) / Prescription opiates (5) / Heroin (6) / LSD (acid) (7) / Magic mushrooms (8) / DMT (9) / Synthetic hallucinogens – e.g. 2-CB, 25I-NBOMe (10) / Tobacco/tobacco products (11) / Cocaine (12) / Amphetamine (e.g. 'speed') (13) / Ecstasy/MDMA (14) / Spanglers (15) / 4-FA (16) / MDA (17) / Mephedrone (18) / Nitrous oxide ('laughing gas') (19) / GHB (20) / Ketamine (21) / Synthetic dissociatives (e.g. methoxetamine) (22) / Amyl/alkyl nitrates ('poppers') (23) / Other (24) / I have never used alcohol or other drugs

<If never tried drugs, move to 14>

<12.ii – 13 asked for each drug ever used>

12.ii How old were you when you first tried this drug?

- <integer input>

12.iii How often did you use this drug in the last 12 months?

- Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1) / Not in the last 12 months (0)

<if select not in last 12 months (0), ask 12.iii.a, otherwise move to 12.iv>

12.iii.a How old were you when you last used this drug?

- *<integer input>*

12.iv At what age was your use of this drug the heaviest? If you have used it only once or twice in your life, or if your use has been consistence since the age you first tried it, then please enter the age you first used until the age you most recently used

- Age: *<integer input>* years to *<integer input>* years

12.v During this period of heaviest use, how frequently did you use this drug?

- Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1)

13. Where do you use this drug most often? *<For each drug used in the last 12 months 12.iii>*

- Nightclubs (1) / Licensed: festivals/outdoor parties/raves (2) / Illegal: festivals/outdoor parties/raves (3) / Pubs/bars (4) / House party (5) / At home/friend's house (6) / Outside/in public spaces e.g. parks (7) / Other *<if selected>* Please specify

<14 only to be shown to those indicating use of MDMA/ecstasy in the last 12 months in 12.iii>

14.i On how many days in the past 12 months did you use ecstasy pills/tablets?

- *<integer input>*

< if 14.i>0 show 14.i.a >

14.i.a How many ecstasy pills/tablets do you use on a night that you use ecstasy pills/tablets?

- Ecstasy pills/tablets: *<up/down buttons in quarter pill intervals>*

14.ii On how many days in the past 12 months did you use MDMA crystal/powder?

- *<integer input>*

<if 14.ii>0 show 14.ii.a >

14.ii.a How much MDMA crystal/powder do you use on a night that you use MDMA crystal/powder?

- MDMA crystal/powder: *<up/down buttons in 100 milligram intervals>*

<if 14.i>0 and 14.ii>0 additionally show 14.iii>

14.iii On how many occasions in the past 12 months did you use both ecstasy pills/tablets and MDMA powder/crystal at the same time?

- *<integer input>*

< if 14.iii>0 show 14.iii.a >

14.iii.a On these occasions when you use both, how many ecstasy pills/tablets and how much MDMA crystal/powder do you use?

- Ecstasy pills/tablets: *<up/down buttons in quarter pill intervals>*
- MDMA crystal/powder: *<up/down buttons in 100 milligram intervals>*

15. Please complete these questions even if you do not use drugs other than alcohol and/or tobacco: If you were to change your overall drug use in the next 12 months, how important would the following influences be on your decision to change your use?

<not important (0) / not very important (1) / slightly important (2) / very important (3)>

- Changes in my financial situation / Changes in the price of drugs that I use / Changes in the purity of drugs that I use / Changes in the availability of drug testing services / Changes in

how easy or difficult it is to take this drug at a dance/electronic music event / Learning new information about the drugs that I use / Finding another substance that I prefer / Effects on my physical health / Effects on my psychological health / Personally, or someone I know, having a particularly good experience / Personally, or someone I know, having a particularly bad experience / Trouble balancing weekend and week responsibilities / Having or planning children / Other family commitments / Fear of legal consequences / Legislative changes in relation to the drugs that I use / Recognising that I should control my drug use / Being asked to change by family/friends/partner / Drug screening in your school/university or place of work

16. Do you intend to change your alcohol and/or other drug use in the next 12 months?

- Yes – I intend to increase my use a lot (2) / Yes - I intend to increase my use a little (1) / No – I intend my use to stay the same (0) / Yes - I intend to decrease my use a little (-1) / Yes – I intend to decrease my use a lot (-2) / Yes - I intend to stop using alcohol and/or drugs (-3)

<AUDIT-C: 17.i – 17.iii only to be shown to those who selected alcohol in 12.i>

17.i How often do you have a drink containing alcohol?

- Never (0) / Monthly or less (1) / 2 – 4 times per month (2) / 2 – 3 times per week (3) / 4+ times per week (4)

17.ii. How many alcoholic drinks do you drink on a typical day when you are drinking?

- 1 – 2 (0) / 3 – 4 (1) / 5 – 6 (2) / 7 – 9 (3) / 10+ (4)

17.iii. How often did you have 6 or more drinks on a single occasion in the last year?

- Never (0) / Less than monthly (1) / Monthly (2) / Weekly (3) / Daily or almost daily (4)

<DUDIT to be shown to those indicating use of drugs other than alcohol in 12.i>

18. Please answer the following 11 questions in reference to the drugs that you used in the last 12 months, as indicated above. Please answer as correctly and honestly as possible by indicating which answer is right for you.

i. How often do you use drugs other than alcohol?

- Never (0) / Once a month or less often (1) / 2-4 times a month (2) / 2-3 times a week (3) / 4 times a week or more often (4)

ii. Do you use more than one type of drug on the same occasion?

- Never (0) / Once a month or less often (1) / 2-4 times a month (2) / 2-3 times a week (3) / 4 times a week or more often (4)

iii. How many times do you take drugs on a typical day when you use drugs?

- 0 (0) / 1 – 2 (1) / 3 – 4 (2) / 5 – 6 (3) / 7 or more (4)

iv. How often are you influenced heavily by drugs?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

v. Over the last year, have you felt that your longing for drugs was so strong that you could not resist it?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

vi. Has it happened, over the past year, that you have not been able to stop taking drugs once you started?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

vii. How often over the past year have you taken drugs and then neglected to do something you should have done?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)
- viii. How often over the past year have you needed to take a drug the morning after heavy drug use the day before?
- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)
- ix. How often over the past year have you had guilt feelings or a bad conscience because you used drugs?
- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)
- x. Have you or anyone else been hurt (mentally or physically) because you used drugs?
- No (0) / Yes, but not over the past year (1) / Yes, over the past year (2) /
- xi. Has a relative or a friend, a doctor or a nurse, or anyone else, been worried about your drug use or said that you should stop using drugs?
- No (0) / Yes, but not over the past year (1) / Yes, over the past year (2)

19.i Please indicate the drugs (maximum of 3) you were thinking of when completing the last 11 questions.

19.ii Please rank these drugs in the order of which you were most thinking about (1=most thought about, 2=second most thought about, and so on)

20. How many of your friends use drugs other than alcohol and tobacco?

- None (0) / Some (1) / Many (2) / Most (3) / All (4)

Risk and experiences

21. How much do you think people risk harming themselves (physically or in other ways), if they...
<no risk (0) / slight risk (1) / moderate risk (2) / great risk (3) / don't know (4)>

- Smoke cigarettes occasionally / Smoke one or more packs of cigarettes per day / Have one or two alcoholic drinks nearly every day / Have four or five alcoholic drinks nearly every day / Have five drinks in one occasion nearly every weekend / Try marijuana or hashish (cannabis) once or twice / Smoke marijuana or hashish (cannabis) occasionally / Smoke marijuana or hashish (cannabis) regularly / Try ecstasy once or twice / Take ecstasy regularly / Try an amphetamine (uppers, pep pills, bennie, speed) once or twice / Take amphetamines regularly

22. In the past 12 months, have you ever experienced any of the following after using drugs other than alcohol or tobacco before, during or after a dance/ electronic music event?

<Sliders ranging from Never (0) to All the time (10)>

- Intense pleasure / Enhanced perception and increased enjoyment of music / Reduced inhibitions / Feelings of love and empathy / Expanded consciousness / Increased sense of enlightenment / Closeness to others / Making new friends
- Memory loss / Vomiting / Agitation / Accidents / Aggression/victim of aggression / Breathing difficulties / Panic attacks/anxiety / Arguments with friends / Overheating / Fainting/collapsing / Inability to move / Sexual activity you later regret / Driven/been driven by someone under the influence of alcohol or drugs / Palpitations / Low mood/anxiety in days afterwards / Problems with a bouncer (e.g. drugs confiscated) / Legal problems (e.g. being arrested) / Seeking/receiving emergency medical treatment / Spending money you cannot afford to / Effect of the drug not as expected / Problems with sleep in days after use / Missing work or other important commitments

23. WHO-5: Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks.
<at no time (0) / some of the time (1) / less than half the time (2) / more than half the time (3) / most of the time (4) / all of the time (5)>

- I have felt cheerful and in good spirits / I have felt calm and relaxed / I have felt active and vigorous / I woke up feeling fresh and relaxed / My daily life has been filled with things that interest me

Harm Reduction

24. In the last 12 months have you implemented any of the following strategies to minimise potential harms from drug use in relation to an electronic dance/ electronic music event?
<answered yes / no>

i. Before use

13. Research new drugs or pills online. / Test your drugs using a home testing kit or testing service. / Get advice on new drugs or batches from a trusted prior user. / Plan what you would do if you or your friends start to feel unwell. / Make prior arrangements about how you will get home. / Take pre-loading substances with the aim of preparing for drug use, such as multivitamins, 5-HTP... / Avoid using if you are depressed, anxious or going through a rough patch. / Eating properly/well before use. / Have a healthy day before going out. / Plan when to take drugs during the evening. / Plan how to get drugs into venue(s). / Set limits on the amount that you use

ii. During use

12. Take a small test dose of a new drug, new batch or drug that you do not know the purity of. / Only use drugs that you have sourced from a trusted dealer or friend. / Tell someone what you have taken. / Keep an eye on your friends and others. / Drink a safe amount of water. / Avoid combining illicit drugs and/or alcohol. / Take regular breaks from physical activity, such as dancing, to 'chill out'. / Avoid sharing tubes/straws/notes/keys/cards when sniffing. / Avoid using drugs intravenously. / Chewing candy or gum to avoid teeth grinding. / Keeping your drug use in line with what you would consider 'normal' (i.e. recreational, sensible and controlled).

iii. After use

8. Eat properly/well on the morning/day after use. / Taking post-loading substances with the aim of recovering and/or dealing with hangovers/comedowns, such as multivitamins, 5-HTP, fruit juice, milk, sleeping tablets / Take regular breaks from drug use. / Avoid driving under the influence. / Maintaining a healthy lifestyle, with regard to sleep, exercise and diet. / Catching up on lost sleep. / Contact friends the next day to see if they are ok.

Demographics 2

25. Are you

- Only attracted to women (1) / Mostly attracted to women (2) / Equally attracted to women and men (3) / Mostly attracted to men (4) / Only attracted to men (5) / Not attracted to men nor women (6) / Prefer not to say (7)

26. Are you

- Single (1) / Married or in a civil partnership (2) / Divorced or separated (3) / In a relationship not living with partner (4) / In a relationship and living with partner (5) / Widow(er) (6)

27. What is your current occupation (please tick all that apply)?

- Full time work (1) / Part time work (2) / Student (3) / Neither in education, employment or training (4)

28. Where do you currently live?

- Large town/City (1) Small to mid-sized town (2) Rural/countryside (3)

29. What is the highest educational level you have attained?

<completed (2) / currently attending (1) / never started (0)>

- Primary school – key stage 1 and 2 (1) / Comprehensive, grammar or secondary school years 1 to 3 – key stage 3 (2) / GCSE/A Level/GNVQs/NVQs 1-3 – key stage 4 (3) / Sub-degree/NVQ4/Undergraduate degree/Master's degree/doctorate (4)

30. What is the highest educational level **your mother** attained?

<completed (2) / currently attending (1) / never started (0)>

- Primary school – key stage 1 and 2 (1) / Comprehensive, grammar or secondary school years 1 to 3 – key stage 3 (2) / GCSE/A Level/GNVQs/NVQs 1-3 – key stage 4 (3) / Sub-degree/NVQ4/Undergraduate degree/Master's degree/doctorate (4)

Appendix 2 – EMSS Follow-up items

Demographics 1

1. How old are you? years
2. What is your gender?
 - Male (1) / Female (2) / Other (3)
3. Which country do you currently live in?
 - UK (1) / Netherlands (2) / Belgium (3) / Sweden (4) / Italy (5) / Other (6)
4. What is your area code, i.e. the first 3 or 4 characters of your postcode? For example, if your postcode is WC1E 7HB enter 'WC1E'. This question is optional
 - *Free text input*

Nightlife

5. How many times did you attend a dance/ electronic music event in the last 12 months?
6. On average, how often are the following genres of music played at dance/electronic music events you attend? If you have not heard of a certain music genre, please still respond by using the slider to select 'Never'
<Sliders ranging from "Never" to "All the time">
 - House / Dubstep / Hard dance / Hardcore / Gabba / Techno / Trance / Goa-trance / Psy-trance / Drum 'n' bass / Jungle / Hip hop / R 'n' B / Reggae / Dancehall / Ragga / Ska / Electro / IDM / Experimental / New wave / Disco / Other
7. How important (**for you**) are the following reasons to go to a dance/ electronic music event?
<Not important (0) / Not very important (1) / Slightly important (2) / very important (3)>
 - To dance / My friends are going / To meet new people / To look for sex / To look for a partner / To escape my daily life / To take drugs / To drink alcohol / To have fun / To listen to music / To explore my mind / To seek excitement / To cope with my problems / To open up to my friends / To see a particular artist or event
- 8.i Which of the following events or venues have you ever attended in the last 12 months?
<radio buttons of following events/venues:>
 - Nightclubs (1) / Licensed: festivals/outdoor parties/raves (2) / Illegal: festivals/outdoor parties/raves (2) / Pubs/bars (4) / House party/party at a friend's house (5) / None of the above (0)
<9 – 10 asked for each event or venue ever attended>
9. How old were you when you first attended this event or venue?
 - *<integer input>*
10. How often did you attend this event or venue in the last 12 months?
 - Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1) /
11. How many of your friends go to dance/ electronic music events at least 6 times in the last 12 months?

- None (0) / Some (1) / Many (2) / Most (3) / All (4)

Drug use

12. Have you used any of the following drugs in the last 12 months? (yes/no)

- Alcohol (1) / Cannabis (2) / Synthetic cannabinoids (e.g. 'Spice') (3) / Benzodiazepines (e.g. Valium) (4) / Prescription opiates (5) / Heroin (6) / LSD (acid) (7) / Magic mushrooms (8) / DMT (9) / Synthetic hallucinogens – e.g. 2-CB, 25I-NBOMe (10) / Tobacco/tobacco products (11) / Cocaine (12) / Amphetamine (e.g. 'speed') (13) / Ecstasy/MDMA (14) / Spanglers (15) / 4-FA (16) / MDA (17) / Mephedrone (18) / Nitrous oxide ('laughing gas') (19) / GHB (20) / Ketamine (21) / Synthetic dissociatives (e.g. methoxetamine) (22) / Amyl/alkyl nitrates ('poppers') (23) / 6-ABP/benzo fury (24) / Ritalin (25) / salvia/salvia divinorum (26) / fentanyl/fentanyl like substances (27) / Other (28) / I have not used alcohol or other drugs in the past 12 months

<If not used drugs in past 12 months, move to 23>

13. Please list any other drugs you have taken (or leave blank if none).

<14 – 16 asked for each drug ever used>

14. How old were you when you first tried this drug?

- *<integer input>*

15. How often did you use this drug in the last 12 months?

- Three times a week or more (6) / Weekly (5) / Fortnightly (4) / Monthly (3) / Every two or three months (2) / Three times or less in the year (1) / Not in the last 12 months (0)

16. Where do you use this drug most often? *<For each drug used in the last 12 months 12.iii>*

- Nightclubs (1) / Licensed: festivals/outdoor parties/raves (2) / Illegal: festivals/outdoor parties/raves (3) / Pubs/bars (4) / House party (5) / At home/friend's house (6) / Outside/in public spaces e.g. parks (7) / Other *<if selected>* Please specify

<17 - 22 only to be shown to those indicating use of MDMA/ecstasy in the last 12 months in 12>

17 On how many days in the past 12 months did you use ecstasy pills/tablets?

- *<integer input>*

<if 17>0 show 18>

18. How many ecstasy pills/tablets do you use on a night that you use ecstasy pills/tablets?

- Ecstasy pills/tablets: *<up/down buttons in quarter pill intervals>*

19. On how many days in the past 12 months did you use MDMA crystal/powder?

- *<integer input>*

<if 19>0 show 20>

20. How much MDMA crystal/powder do you use on a night that you use MDMA crystal/powder?

- MDMA crystal/powder: *<up/down buttons in 100 milligram intervals>*

<if 17>0 and 19>0 additionally show 21>

21. On how many occasions in the past 12 months did you use both ecstasy pills/tablets and MDMA powder/crystal at the same time?

- *<integer input>*

<if 21>0 show 22>

22. On these occasions when you use both, how many ecstasy pills/tablets and how much MDMA crystal/powder do you use?

- Ecstasy pills/tablets: *<up/down buttons in quarter pill intervals>*
- MDMA crystal/powder: *<up/down buttons in 100 milligram intervals>*

23. Do you intend to change your alcohol and/or other drug use in the next 12 months?

- Yes – I intend to increase my use a lot (2) / Yes - I intend to increase my use a little (1) / No – I intend my use to stay the same (0) / Yes - I intend to decrease my use a little (-1) / Yes – I intend to decrease my use a lot (-2) / Yes - I intend to stop using alcohol and/or drugs (-3)

24. Have you changed you alcohol use in the last 12 months?

- Yes – I have increased it a lot (2) / Yes – I have increased it a little (1) / No – it has stayed the same (0) / Yes – it has decreased a little (-1) / Yes – it has decreased a lot (-2) / Yes – I stopped using alcohol (-3)

25. Have you changed you use of drugs other than alcohol and tobacco in the last 12 months?

- Yes – I have increased it a lot (2) / Yes – I have increased it a little (1) / No – it has stayed the same (0) / Yes – it has decreased a little (-1) / Yes – it has decreased a lot (-2) / Yes – I stopped using drugs (-3)

26. Please indicate the drugs (maximum of 3) you were thinking of when completing the last question

27.i Please think about your drug use in the last 12 months. Have you experienced any of the following in the last 12 months?

<each to be answered Yes (1) / No (0)>

- Changes in my financial situation / Changes in the price of drugs that I use / Changes in the purity of drugs that I use / Changes in the availability of drug testing services / Changes in how easy or difficult it is to take this drug at a dance/electronic music event / Learning new information about the drugs that I use / Finding another substance that I prefer / Effects on my physical health / Effects on my psychological health / Personally, or someone I know, having a particularly good experience / Personally, or someone I know, having a particularly bad experience / Trouble balancing weekend and week responsibilities / Having or planning children / Other family commitments / Legal consequences / Legislative changes in relation to the drugs that I use / Recognising that I should control my drug use / Being asked to change by family/friends/partner / Drug screening in your school/university or place of work

<27.ii only to be shown to those who answered anything other than 'No... (0)' to 25>

<for each item answered 'Yes' in Q27.i ask Q27.ii if Q25 is not 0>

27.ii How important was this experience in influencing decisions to change your drug use?

- Not important (0) / Not very important (1) / Slightly important (2) / Very important (3)

<AUDIT-C: 28.i – 28.iii only to be shown to those who selected alcohol in 12>

28.i How often do you have a drink containing alcohol?

- Never (0) / Monthly or less (1) / 2 – 4 times per month (2) / 2 – 3 times per week (3) / 4+ times per week (4)

28.ii. How many alcoholic drinks do you drink on a typical day when you are drinking?

- 1 – 2 (0) / 3 – 4 (1) / 5 – 6 (2) / 7 – 9 (3) / 10+ (4)

28.iii. How often did you have 6 or more drinks on a single occasion in the last year?

- Never (0) / Less than monthly (1) / Monthly (2) / Weekly (3) / Daily or almost daily (4)

<DUDIT 29 – 30.ii to be shown to those indicating use of drugs other than alcohol in 12.i>

29. Please answer the following 11 questions in reference to the drugs that you used in the last 12 months, as indicated above. Please answer as correctly and honestly as possible by indicating which answer is right for you.

i. How often do you use drugs other than alcohol?

- Never (0) / Once a month or less often (1) / 2-4 times a month (2) / 2-3 times a week (3) / 4 times a week or more often (4)

ii. Do you use more than one type of drug on the same occasion?

- Never (0) / Once a month or less often (1) / 2-4 times a month (2) / 2-3 times a week (3) / 4 times a week or more often (4)

iii. How many times do you take drugs on a typical day when you use drugs?

- 0 (0) / 1 – 2 (1) / 3 – 4 (2) / 5 – 6 (3) / 7 or more (4)

iv. How often are you influenced heavily by drugs?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

v. Over the last year, have you felt that your longing for drugs was so strong that you could not resist it?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

vi. Has it happened, over the past year, that you have not been able to stop taking drugs once you started?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

vii. How often over the past year have you taken drugs and then neglected to do something you should have done?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

viii. How often over the past year have you needed to take a drug the morning after heavy drug use the day before?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

ix. How often over the past year have you had guilt feelings or a bad conscience because you used drugs?

- Never (0) / Less than once a month (1) / Every month (2) / Every week (3) / Daily or almost every day (4)

x. Have you or anyone else been hurt (mentally or physically) because you used drugs?

- No (0) / Yes, but not over the past year (1) / Yes, over the past year (2) /

xi. Has a relative or a friend, a doctor or a nurse, or anyone else, been worried about your drug use or said that you should stop using drugs?

- No (0) / Yes, but not over the past year (1) / Yes, over the past year (2)

30.i Please indicate the drugs (maximum of 3) you were thinking of when completing the last 11 questions.

30.ii Please rank these drugs in the order of which you were most thinking about (1=most thought about, 2=second most thought about, and so on)

31. How many of your friends use drugs other than alcohol and tobacco?

- None (0) / Some (1) / Many (2) / Most (3) / All (4)

Risk and experiences

32. How much do you think people risk harming themselves (physically or in other ways), if they...

<no risk (0) / slight risk (1) / moderate risk (2) / great risk (3) / don't know (4)>

- Smoke cigarettes occasionally / Smoke one or more packs of cigarettes per day / Have one or two alcoholic drinks nearly every day / Have four or five alcoholic drinks nearly every day / Have five drinks in one occasion nearly every weekend / Try marijuana or hashish (cannabis) once or twice / Smoke marijuana or hashish (cannabis) occasionally / Smoke marijuana or hashish (cannabis) regularly / Try ecstasy once or twice / Take ecstasy regularly / Try an amphetamine (uppers, pep pills, bennie, speed) once or twice / Take amphetamines regularly

33. In the past 12 months, have you ever experienced any of the following after using drugs other than alcohol or tobacco before, during or after a dance/ electronic music event?

<Sliders ranging from Never (0) to All the time (10)>

- Intense pleasure / Enhanced perception and increased enjoyment of music / Reduced inhibitions / Feelings of love and empathy / Expanded consciousness / Increased sense of enlightenment / Closeness to others / Making new friends
- Memory loss / Vomiting / Agitation / Accidents / Aggression/victim of aggression / Breathing difficulties / Panic attacks/anxiety / Arguments with friends / Overheating / Fainting/collapsing / Inability to move / Sexual activity you later regret / Driven/been driven by someone under the influence of alcohol or drugs / Palpitations / Low mood/anxiety in days afterwards / Problems with a bouncer (e.g. drugs confiscated) / Legal problems (e.g. being arrested) / Seeking/receiving emergency medical treatment / Spending money you cannot afford to / Effect of the drug not as expected / Problems with sleep in days after use / Missing work or other important commitments

34. Thinking about your country in general, how socially acceptable do you think drug use is?

<scale from very unacceptable (0) to very acceptable (10)>

35. Thinking about your country in general, have you noticed changes to the social acceptability of drug use in the past 12 months?

<scale from become less unacceptable (0) to become more acceptable (10)>

<36 – 37 only to be shown to those indicating use of drugs other than alcohol or tobacco in 12>

36. When weighing up the pros and cons of your drug use, would you say that using your drugs contributes to your life in a positive or negative way?

<scale from completely negative (0) to completely positive (10)>

37. How much did you worry about your use of drugs in the last 12 months?

- Not at all (0) / A little (1) / Often (2) / Always or nearly always (3)

38. WHO-5: Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks.

<at no time (0) / some of the time (1) / less than half the time (2) / more than half the time (3) / most of the time (4) / all of the time (5)>

- I have felt cheerful and in good spirits / I have felt calm and relaxed / I have felt active and vigorous / I woke up feeling fresh and relaxed / My daily life has been filled with things that interest me

39. PHQ2 and GAD2: Over the past 2 weeks, how often have you been bothered by the following problems:

<not at all (0) / several days (1) / more than half the days (2) / nearly every day (3)>

- Little interest or pleasure in doing things / feeling down, depressed or hopeless / feeling nervous, anxious or edgy / not being able to stop or control worrying

Harm Reduction

40. In the last 12 months have you implemented any of the following strategies to minimise potential harms from drug use in relation to an electronic dance/ electronic music event?

<answered yes / no>

i. Before use

14. Research new drugs or pills online. / Test your drugs using a home testing kit or testing service. / Get advice on new drugs or batches from a trusted prior user. / Plan what you would do if you or your friends start to feel unwell. / Make prior arrangements about how you will get home. / Take pre-loading substances with the aim of preparing for drug use, such as multivitamins, 5-HTP... / Avoid using if you are depressed, anxious or going through a rough patch. / Eating properly/well before use. / Have a healthy day before going out. / Plan when to take drugs during the evening. / Plan how to get drugs into venue(s). / Set limits on the amount that you use

ii. During use

13. Take a small test dose of a new drug, new batch or drug that you do not know the purity of. / Only use drugs that you have sourced from a trusted dealer or friend. / Tell someone what you have taken. / Keep an eye on your friends and others. / Drink a safe amount of water. / Avoid combining illicit drugs and/or alcohol. / Take regular breaks from physical activity, such as dancing, to 'chill out'. / Avoid sharing tubes/straws/notes/keys/cards when sniffing. / Avoid using drugs intravenously. / Chewing candy or gum to avoid teeth grinding. / Keeping your drug use in line with what you would consider 'normal' (i.e. recreational, sensible and controlled).

iii. After use

9. Eat properly/well on the morning/day after use. / Taking post-loading substances with the aim of recovering and/or dealing with hangovers/comedowns, such as multivitamins, 5-HTP, fruit juice, milk, sleeping tablets / Take regular breaks from drug use. / Avoid driving under the influence. / Maintaining a healthy lifestyle, with regard to sleep, exercise and diet. / Catching up on lost sleep. / Contact friends the next day to see if they are ok.

Demographics 2

41. Are you

- Single (1) / Married or in a civil partnership (2) / Divorced or separated (3) / In a relationship not living with partner (4) / In a relationship and living with partner (5) / Widow(er) (6)

42. What is your current occupation (please tick all that apply)?

- Full time work (1) / Part time work (2) / Student (3) / Neither in education, employment or training (4)

43. Where do you currently live?

- Large town/City (1) Small to mid-sized town (2) Rural/countryside (3)

44. What is the highest educational level you have attained?

<completed (2) / currently attending (1) / never started (0)>

- Primary school – key stage 1 and 2 (1) / Comprehensive, grammar or secondary school years 1 to 3 – key stage 3 (2) / GCSE/A Level/GNVQs/NVQs 1-3 – key stage 4 (3) / Sub-degree/NVQ4/Undergraduate degree/Master's degree/doctorate (4)

46. What is the highest educational level **your mother** attained?

<completed (2) / currently attending (1) / never started (0)>

- Primary school – key stage 1 and 2 (1) / Comprehensive, grammar or secondary school years 1 to 3 – key stage 3 (2) / GCSE/A Level/GNVQs/NVQs 1-3 – key stage 4 (3) / Sub-degree/NVQ4/Undergraduate degree/Master's degree/doctorate (4)

46. Are you

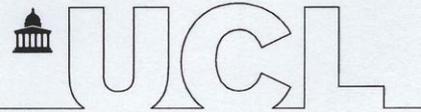
Only attracted to women (1) / Mostly attracted to women (2) / Equally attracted to women and men

(3) / Mostly attracted to men (4) / Only attracted to men (5) / Not attracted to men nor women (6) /

Prefer not to say (7)

Appendix 3 – Ethical approval for EMSS

UCL RESEARCH ETHICS COMMITTEE
ACADEMIC SERVICES



6th March 2017

Professor Valerie Curran
UCL Research Department of Clinical, Educational and Health Psychology

Dear Professor Curran

Notification of Ethical Approval

Re: Ethics Application 10437/001: ALAMA Nightlife Study

I am pleased to confirm in my capacity as Chair of the UCL Research Ethics Committee that I have ethically approved your study until **31st December 2018**.

Approval is subject to the following conditions:

Notification of Amendments to the Research

You must seek Chair's approval for proposed amendments (to include extensions to the duration of the project) to the research for which this approval has been given. Ethical approval is specific to this project and must not be treated as applicable to research of a similar nature. Each research project is reviewed separately and if there are significant changes to the research protocol you should seek confirmation of continued ethical approval by completing the 'Amendment Approval Request Form':
<http://ethics.grad.ucl.ac.uk/responsibilities.php>

Adverse Event Reporting – Serious and Non-Serious

It is your responsibility to report to the Committee any unanticipated problems or adverse events involving risks to participants or others. The Ethics Committee should be notified of all serious adverse events via the Ethics Committee Administrator (ethics@ucl.ac.uk) immediately the incident occurs. Where the adverse incident is unexpected and serious, the Chair or Vice-Chair will decide whether the study should be terminated pending the opinion of an independent expert. For non-serious adverse events the Chair or Vice-Chair of the Ethics Committee should again be notified via the Ethics Committee Administrator within ten days of the incident occurring and provide a full written report that should include any amendments to the participant information sheet and study protocol. The Chair or Vice-Chair will confirm that the incident is non-serious and report to the Committee at the next meeting. The final view of the Committee will be communicated to you.

Final Report

At the end of the data collection element of your research we ask that you submit a very brief report (1-2 paragraphs will suffice) which includes in particular issues relating to the ethical implications of the research i.e. issues obtaining consent, participants withdrawing from the research, confidentiality, protection of participants from physical and mental harm etc.

Yours sincerely



Professor Michael Heinrich
Interim Chair, UCL Research Ethics Committee

Appendix 4 – Online article written for *the Guardian*

Just say 'know' to drugs: can testing facilities make festivals safer?

Drug testing is increasingly becoming part of UK festivals and clubs. Could it be an effective way to change behaviour and reduce the harmful effects of drugs?

For the first time, people going to **BoomTown** this weekend will be able to find out what's in the drugs they plan to take, by getting them tested by non-profit organisation **The Loop**. Front of house drugs safety testing, or Multi Agency Safety Testing (MAST), was first offered by **The Loop at Secret Garden Party and Kendal Calling in 2016**. This was such a success that they have been invited to provide their service at a number of festivals this year, BoomTown being the next on the calendar.

A growing number of festivals are now openly discussing a new approach to drugs, based on information and harm reduction rather than criminal justice. This shift in attitudes is coming at a very welcome time. Recent developments in the European drug market have seen an **unprecedented rise in the strength of ecstasy tablets**, with a number of recent reports of adverse health effects, including emergency medical treatment and fatalities, attributed to MDMA toxicity. Indeed, **Office for National Statistics figures** show an eightfold increase in deaths related to ecstasy in five years, rising to 63 in 2016 from an all-time low of 8 in 2010.

Without specialist drug testing services it is very difficult for drug users to know what they are taking, particularly with regard to potency and purity. Essentially, they have to rely on word of mouth and potentially inaccurate reports based on indicators such as colours or logos on tablets. These methods are unreliable and potentially life threatening. As high quality pills with a distinctive logo and colour develop a good reputation among users, other manufacturers will copy these designs to increase their profits, while changing the contents of the pill. Given that festivals and drug use go hand in hand for a number of people, services such as The Loop that offer drugs safety testing without the fear of criminal sanction would appear vital to avoid health related problems.

The importance of The Loop's service has already been **demonstrated this year**, with their detection of the stimulant N-ethyl-pentylone – being missold as MDMA – which was reportedly causing medical incidents at Kendal Calling. The Loop was able to issue an alert with a description of the blue “Anonymous” pill, and this was circulated on social media by the festival and other on-site agencies so as to warn other potential users of their findings. This new approach replaces the traditional message of ‘just say no to drugs’, with timely, relevant and evidence-based advice: just say ‘*know*’.

The question is, therefore, do services like The Loop actually change behaviour and reduce harm? There is surprisingly little research, despite drugs safety testing being a mainstay in some European countries, such as the Netherlands, for years. A study examining whether such services do actually result in changes in behaviour was **published earlier this year**. Analysing data collected at music events in the USA by drugs testing company, **DanceSafe**, the authors found that people whose samples contained something other than MDMA were far less likely to report that they intended to use the drug as those whose samples were positive for MDMA. In other words, being told that the samples contained something unexpected resulted in people saying they would be less likely to take that drug. However, the method used by DanceSafe to test for the presence of MDMA – colorimetric reagent kits – can say only whether MDMA is likely to be present or not, and cannot determine the strength of the pills. The Loop, meanwhile, offers much more comprehensive testing, including infrared and ultraviolet spectroscopy, all conducted by PhD level chemists.

The Loop itself is also evaluating whether its services actually change people's behaviour towards safer drug use practices, as part of an ongoing research project with Durham University. Their preliminary results are looking promising: last year one in five people handed over drugs to be disposed of after receiving their test results and the harm reduction advice they received. Moreover, this year at Kendal Calling, four in 10 reported that they now intended to use a lower dose after using the service. This is a particularly important outcome, given that the increasing rate of ecstasy-related deaths in the UK has been attributed to high strength pills leading to overdose.

Of course, drugs safety testing is not without limitations. For instance, just because the tested sample doesn't appear to contain any harmful adulterants, there is no guarantee that all the pills in your pocket are definitely 'clean' - pill content and strength can vary even in the same batch. Additionally no drug is completely safe, and knowing what's in your drugs doesn't mean you won't experience problems. For these reasons The Loop's test results are reported back within a structured harm reduction session – delivered by clinically experienced substance misuse practitioners – during which they draw attention to these limitations. Future research should also focus on how test results are interpreted by festivalgoers, and whether people take on board these cautions.

Initial reports from The Loop about the effectiveness of their service, along with the study from the USA are encouraging, but further quantitative research is required in the UK and Europe to conclusively say that this approach works. The Loop will continue to collate and analyse quantitative data to aid that evaluation.

At UCL we are currently running a study into the nightlife scene in partnership with a number of institutions in Europe, including the **Trimbos Institute**, which pioneered the use of drug testing facilities as a harm reduction tool in the Netherlands – indeed, The Loop hopes to compare their findings with the Trimbos testing database. Our study includes an online survey that is currently live, and we will follow up respondents next year using another survey. Harm reduction, including the use of testing services, forms a major component of our survey and we believe it is crucial to compare how people in the UK and elsewhere in Europe respond to these initiatives. For this reason we'd like as many people who attend festivals or who go clubbing anywhere across the UK, to complete the survey. Head to our **website** now if you would like to take part.

Jon Waldron, Claire Mokrysz, Meryem Grabski and Tom Freeman are academic researchers based at University College London and King's College London. They are currently leading a longitudinal study on drug use in the UK and European nightlife scene. To find out more about the study and to take part, please visit www.emssurvey.eu. Fiona Measham is the director of The Loop and professor of Criminology at Durham University

Appendix 5 – EMSS Participant Information Sheet and Consent

Electronic Music Scene Survey (EMSS)

Information Sheet

We would like to invite you to participate in a study about the European nightlife scene. Taking part is entirely voluntary, and you can decide to stop at any stage.

Please read the following information sheet carefully before deciding whether to take part. You can contact the research team by clicking [here](#) if you have any further questions.

About the Electronic Music Scene Survey

This study aims to gather information about the nightlife scene in five European countries – UK, Netherlands, Belgium, Sweden and Italy. We are also interested in alcohol and/or other drug use, but we still want to hear your views and experiences - whether or not you ever consume alcohol and/or other drugs.

There are two surveys in this study. The first is being run now. The second will be launched one year later (the follow up survey). We would like you to take part in both surveys. This will enable us to investigate changes in nightlife engagement over time.

What happens if I decide to take part?

In order to take part, you must be between 18 and 34 years old. You must also have attended at least 6 dance/ electronic music events in the last 12 months. By dance/ electronic music event, we mean any club night, festival, rave etc. that you have attended that played music that could be broadly described as ‘dance’ or ‘electronic’. You must also currently live in either the UK, Netherlands, Belgium, Sweden or Italy.

If you do decide to take part, you will be asked to confirm that you meet the inclusion criteria above. You will also be asked to provide consent for your data to be used in our research, and for us to contact you in a year’s time to invite you to take part in the follow up survey. You will be asked to provide an email address. We will use this to contact you to ask you to complete the second survey in a year’s time. We will only ask for your email address and not for your name, address or any other contact details. Your email address will be stored separately from your survey responses.

When you have provided your consent and a contact email address, you will be re-directed to the start of the survey. The surveys will take approximately 30 minutes to complete. Taking part is entirely voluntary, and you are able to withdraw your participation at any stage. If you wish to withdraw, email the research team and your data will be deleted.

We are also currently planning a single, additional paid study related to this survey. You may be eligible to take part in this additional study, depending on some of your answers to this survey. We will ask you whether you consent to being contacted via the email you provide about taking part in this additional study if you are eligible. You do not have to consent to this to take part in the survey.

What kind of questions will I be asked?

Most questions will focus on your attendance at various nightlife events, alcohol and/or other drug use. We want to know the positive as well as the negative effects of drug use in nightlife settings, and reasons behind your decisions about whether or not you use alcohol and/or other drugs.

You will also be asked for some demographic information such as your age and gender, and questions about your health.

What are the benefits or risks in participating?

You will be entered into a prize draw for completing the first online survey. Winners will be notified by email. Available prizes include 3 MacBook Airls (13-inch 128 GB); 3 Apple iPads (Air 2); 3 Bluetooth speakers (UE Boom2); and 45 £20 gift vouchers.

The first 1000 people per country to complete the follow up survey in 2018 will receive a £20 Amazon gift voucher, and everyone who completes the follow up will be entered into a prize draw. Available prizes include 6 MacBook Airls (13-inch 128 GB); 6 Apple iPads (Air 2); and 15 Bluetooth speakers (UE Boom2).

Another incentive for you to take part is furthering the understanding of the European nightlife scene. The information you provide will be used to write national reports and scientific papers. We hope this information will help to improve the nightlife scene and make it safer for people who use alcohol and/or other drugs.

There are no foreseeable risks in participating in the survey. Your responses will be stored anonymously and will not be linked to your email address. We do not collect your IP address, and you can withdraw your participation at any stage.

Will the information I provide be kept confidential?

Both online surveys are hosted by Qualtrics, which ensures secure and encrypted data capture and storage. Data will be stored on servers that are physically located in the EU, and will not leave the EU.

All of the answers you provide will remain anonymous and strictly confidential. Your responses to the survey and your email address will be stored on physically separate servers. Your email address will be used only to contact you in one year's time to invite you to participate in the follow up survey, and to inform you if you qualify for the £20 voucher or are selected in the prize draws. If you are selected in the prize draws then we will then ask for further contact details to allow us to post the prize. If you consent, we will use the same email to contact you about the additional paid study if you are eligible.

Only a small number of researchers in the five countries will have access to your contact information. You can find out more about these researchers [here](#). Under certain circumstances, we may share fully anonymised data, however no one other than the research teams involved in data collection will ever be given access to your contact information.

The UK Data Protection Act 1998 will apply to all information collected and stored during the study. Data and email addresses will be stored as encrypted, password secured digital computer files and on encrypted cloud based servers located in the EU.

How is the Electronic Music Scene Survey funded?

The Electronic Music Scene Survey is part of the ALAMA Nightlife study, funded by the European Research Area Network on Illicit Drugs (ERANID; <http://www.eranid.eu/projects/alama-nightlife>). It is being run by academic researchers across Europe (UK, Netherlands, Belgium, Sweden and Italy) who are interested in the nightlife scene and drug use. The Clinical Psychopharmacology Unit at University College London, UK, are coordinating the running of the online surveys. You can find out about our work and meet the teams by visiting [our website](#).

This study has received ethical approval from University College London Research Ethic Committee (Project ID: 10437/001).

Any further questions?

If you have any further questions or would like more information about the Electronic Music Scene Survey, please get in touch by [clicking here](#) or using the contact details below:

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Consent

I confirm that I:

- am between 18 and 34 years of age
- have been to dance music events at least 6 times in the last 12 months
- have read the information on the previous page and agree to take part in this study
- consent to being contacted by email in one year for the follow up survey

<yes / no> If yes, enter an email address

I consent to being contacted by email if I may be eligible to participate in an additional, paid study.
<yes / no>.